Modeling Occupant Behavior, Systems Life Cycle Performance, and Energy Consumption Nexus in Buildings Using Multi-Method Distributed Simulation

by

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A dissertation submitted in partial fulfillment of
the requirements for the degree of
Doctor of Philosophy
(Civil Engineering)
in the University of Michigan
2017

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DEDICATION

I dedicate this dissertation to the most important people in my life.

To my parents, *Thomas and Mary* - I owe everything to your support for all my decisions. My wife *Jis*; for being a perennial source of motivation, rejoicing together the highs of life and holding on tight at the times of low. My little ones, *Adiv and Neva*; even though you are unaware of what your Dad is doing right now, you both were my sole source of inspiration. My brothers, *Jimmy and Sajan*; your continuous support is priceless.

Finally, all my friends and family, no words kind enough to express my gratitude towards you all.

You all helped me realize my dream. Thank you!

ACKNOWLEDGMENTS

There was a time in my career that I spent at a construction project site having “wild dreams” about pursuing a Ph.D. I was sure that I had the capability and passion to do it, but realizing a dream like that required support and encouragement from several corners. At this outset, I would like to gratefully acknowledge several individuals who helped me reach this level.

Professor Carol Menassa, as my faculty advisor at UM, provided constant support and invaluable guidance through the past several years. I appreciate all her contributions in terms of ideas, time, and funding to make my Ph.D. experience productive and successful. The knowledge and confidence I acquired over these years is solely because of her mentoring and support. I learned a lot from her in terms of research and conduct, and I am sure I will succeed as a faculty if I could replicate at least 10% of what she is.

I also would like to equally thank Professor Vineet Kamat who helped me realize my passion. It was him who first responded to my pursuit for a Ph.D. position and he provided me constant support from the time I started interacting with him. His mentoring methods and outlook towards life have a significant impact on my overall thematic orientation for the future. He was more like a friend to me, than a professor and I owe a lot to him for the success I had so far.

I also wish to thank the Ph.D. committee members for their invaluable support. Professor SangHyun Lee has constantly mentored me with his guidance, counsel, and support. His unique systems thinking approach has had a major positive influence on this

Ph.D. work. Working with Professor Mathew Plumlee has also been a true pleasure. His statistics based course gave a unique perspective to my research here at UM.

Several University of Michigan graduate students have provided me with unconditional support throughout the course of my Ph.D. I would like to thank; Dr. Aslihan Karatas, Bharadwaj Mantha, Da Li, Kurt Lundeen, Yong Xiao, Mohammad Yardehnavi and Lichao Xu. Special mention to Avinkrishnan, who was a great support for me all through my Ph.D. years.

I would also like to thank Professor Koshy Varghese, Professor K. N. Sathyanarayana and Professor S. R. Gandhi from Indian Institute of Technology, Madras for being role models and constant mentors. Their help had a definite impact on me succeeding in realizing my dream of a Ph.D.

Finally, I wish to acknowledge the financial support for this research received from the US National Science Foundation (NSF) Awards, NSF – 1349921 and NSF-1407908. Any opinions and findings in this dissertation are those of the author and do not necessarily represent those of NSF.

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ABSTRACT

Buildings consume 40% of the total energy produced in the United States (US), making this sector an opportune choice for devising strategies aimed at reducing energy consumption. Even though various tools and simulation frameworks have been developed in prior work for evaluating, monitoring, and regulating the energy use in buildings, their deployment has primarily been in the form of standalone applications that consider limited aspects of the entire system. For example, energy simulation programs provided by the US Department of Energy such as EnergyPlus and eQuest calculate the annual operating energy in a building by assuming static parameters for occupancy schedules and performance of building systems. However, this approach does not consider the effects of occupants' dynamic energy use behavior or the effects of material and systems degradation over the life cycle of a building, among other influencing factors. Therefore, the primary objective of this dissertation is to create a simulation framework that is capable of modeling and analyzing a building's energy consumption with improved accuracy by considering dynamic influencing factors through an interdependent analysis.

A primary contribution of this research effort is the Lightweight and Adaptive Building Simulation (LABS) framework, an innovative distributed computing environment that can conduct a life cycle based building energy simulation by incorporating several dynamic energy-influencing factors in unison. The LABS framework integrates all the energy requirements occurring in a building's life cycle such as embodied, operational and end of life energy demands, thereby visualizing the inter-dependency among these energy requirements and all dynamic influencers affecting a building's life cycle energy profile.

The effectiveness of the LABS framework was evaluated and demonstrated through several case-study analyses. A system dynamics based energy simulation analysis performed on a case study building located in Chicago has shown that energy savings of up to 20.5% are possible by adopting effective operational and maintenance schemes in a building's entire life cycle. Similarly, it has also been demonstrated that influencing occupant behavioral choices through energy based interventions, can achieve energy savings of up to 13% per month. These two observations highlight the importance of analyzing the effects of dynamic factors in a building's life cycle and the capabilities of the LABS framework in analyzing and quantifying the interdependent effects of such factors during a building's life cycle. By allowing coupled effects of multiple energy-influencing processes to be concurrently explored, this research opens future possibilities for the performance-based assessment of building energy systems.

CHAPTER 1

Research Background

1.1 Introduction

World energy consumption is on a rise, and it is estimated that by 2040 there would be a 48% growth from the current consumption levels (IEA 2016). Even though, energy is a critical component in our day-to-day lives, the emissions associated with its production and use account for two-thirds of world's total greenhouse gas (GHG) emissions (IEA 2015), and pose several threats to the environment. The adverse impacts of the environmental emissions include global warming, air and water pollution, damage to the human health and other economic impacts (EPA 2017). Of which, global warming has severe compounding effects such as the altering water supplies, rising sea levels, and more importantly the changing weather patterns (EPA 2016). As a result, the year 2016 has been the warmest year recorded on the earth since modern recordkeeping began in 1880 (NASA2017).

Another concern looming in the energy sector is the continuously depleting non-renewable energy sources. It is now an accepted fact that if the consumption goes as usual, these sources will last for only close to 100 years (WEC 2013). As of 2015, 80% of the total primary energy supply is sourced through non-renewable energy sources (IEA 2016), therefore, we need to bring institutional as well as technological changes that facilitate ways of controlling the energy use. The fastest and the least costly way of addressing the energy related challenges is by increasing the energy efficiency of the different energy consuming processes (IEA 2011).

We divide our energy use among four economic sectors: residential, commercial, transportation, and industrial (DOE 2012). Figure 1-1 below shows the energy consumption share across different sectors in the United States. The commercial and the residential building sector put together continue to be a major consumer of energy (DOE 2012). Additionally, it is estimated that around 30% of the energy in the commercial sector is going as waste due to inefficient and unnecessary use of building facilities (Energy Star 2015). This points to the fact that significant opportunities are available in the building sector to devise measures that help maximize the energy savings. In addition to the focus on achieving energy savings, providing necessary comfort conditions to the occupants is also a prime research importance, as people spent around 92% of their time in indoor building environments (Kim et al. 2015, Yahya et al. 2014, Yun et al. 2012, Klepeis et al. 2001). Therefore, providing comfortable and sustainable living facilities in an energy efficient manner thus becomes an inevitable research requirement.

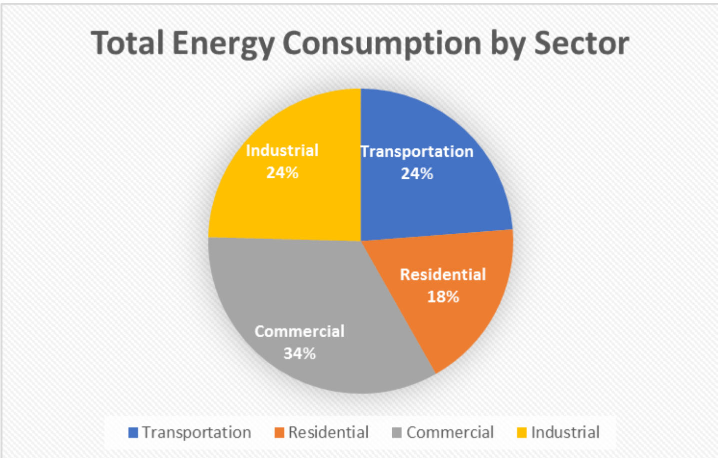

Figure 1-1 Total Energy Consumption by Sector (Adapted from IEA 2016)

1.2 Building energy analysis

Understanding the different energy requirements in a building is foremost requirement to devise energy savings strategies. There are several methods and frameworks currently available, and the literature on building's energy analysis can be generally categorized into two domains. The first domain focuses on analyzing the energy incurred across the distinct phases of a building's life cycle, such as the material manufacturing phase, the construction phase, use and maintenance phase and the end of life phase (Dixit et al. 2010, Bayer et al. 2010), by adopting a life cycle approach. The second set of studies developed co-simulation frameworks to augment the capabilities of existing energy simulation tools. In the below sections, both these approaches are briefly introduced, followed by discussing the barriers and the overall organization of this dissertation.

1.2.1 Life cycle based approaches

The energy requirements in a building's life cycle can be broadly categorized into two types: Embodied energy (EE) and the Operating energy (OE). Embodied energy is the energy required for production of building materials, construction of living facilities, and the energy required for building deconstruction during the end-of-life phase (Dixit et al. 2010). Operating energy (OE) is the energy expended during the use and maintenance phase to maintain the internal environment of the building under livable condition, and constitutes around 80% of the total energy requirements in a building (CSSBI 2013, UNEP 2007).

EE is quantified with the help of several Life Cycle Assessment (LCA) based databases that provide the energy intensity of materials (energy required for producing a unit quantity of a material, usually expressed in Mega Joules/kilo grams) (IES VE 2014, DOE-2.3 2014, Athena Impact Estimator V4.2 2013, ECEB -Moncaster and Symons 2013, Building's Energy Data Book- U.S DOE 2012, GaBi 2012, BEES 2015, SimaPro7 2010 – Goedkoop et al. 2010, ICE Database – Hammond and Jones 2008). These databases are used for estimating the EE for constructing a new building, or for estimating the EE for the replacement of materials during the use and maintenance phase. For estimation of operating energy in a building, the general method adopted is to use the capabilities of energy simulation tools such as EnergyPlus, eQuest, DOE2, Radiance and TRNSYS, among many others. These tools have a simulation engine that predicts the energy related requirements for the heating, cooling, lighting and various plug loads, by taking the basic building details (location, weather specifics, building operating schedules) as inputs. All these tools can do such an energy use estimation for maximum a year period.

The approach taken by the life cycle based studies is to estimate the energy requirements in a building's life cycle by integrating the EE and the OE estimation mechanisms, based on deterministic and static inputs/assumptions. Even though such a deterministic approach is useful in understanding the overall energy requirements in a building's life cycle, one major limitation is that the current body of knowledge do not provide options for analyzing the inter-relationships and feedbacks that exist between the different energy requirements. For instance, replacing the insulation material in an external wall assembly increases the thermal performance of the assembly thereby decreasing the OE requirements. Differently stated, incurring EE for material maintenance and replacement will have definite impact on the building performance and thus on the operating energy performance. However, the current approach assumes that constant annual OE over the entire life cycle of a building. Furthermore, for performing a maintenance or replacement activity, building stakeholders are faced by questions about the optimum time to perform a maintenance/replacement, type of maintenance to be conducted (e.g., minor or major), cost impacts/ energy savings of conducting a maintenance, to name a few. Likewise, a building with a higher IEE (high performing buildings) can yield a better operating energy performance when an overall life cycle is considered. To capture all these important relationships, adopting a systems approach is a desirable choice to understand how strategic decisions (e.g., material selection, maintenance or replacement of materials) needs to be analyzed in tandem.

1.2.2 Co-Simulation based approaches in energy simulation

Co-simulation frameworks are used to represent the energy effects of dynamic actions (e.g., occupant's varying behavioral patterns) in a building's operation. The basic ideology of a co-simulation mechanism is to create simulation modules that model the dynamic components in a building's operation, and couple it with a traditional energy simulation tool. Such an approach is necessary because the current energy simulation programs (e.g., EnergyPlus, eQuest) approximate the various parameters in a building energy model, and therefore do not precisely represent the real-time fluctuations in a building's operation (e.g., real occupancy schedules and energy use patterns). Several co-simulation frameworks are developed for achieving this such as the Building Control Virtual Test Bed, MLE+, High Level Architecture and Functional Mockup Unit (Nouidui et al. 2014, Menassa et al. 2013, Bernal et al. 2012, Wetter 2011). The basic idea of such a framework lies in connecting the basic energy simulation engine with an additional simulation module, and allowing the capability of exchanging variables mutually. Such an analysis gives more opportunities for an energy simulation program to represent the dynamism occurring in a building's operation.

However, in the case of current co-simulation frameworks, there are several limitations. BCVTB and HLA are middleware or software brokers that orchestrate the data transfer between the various components in a coupled system. Both these are inherently complex for facility managers and building practitioners to learn easily and adapt for process improvement. Similarly, BCVTB only supports connectivity with limited tools (Wetter 2011), and adding a simulation program of a designer's choice becomes hard to implement, thereby forcing the user to adhere to the limited capabilities offered by BCVTB/HLA to create various control modules. This dents the chance of the reuse of existing simulation tools created in multiple software platforms. Even though, the recently introduced FMU provides more flexibility, it still does not give the option to connect a module of a designer's choice into the loop. Finally, the general approach adopted in all these frameworks is by defining a master program (usually the energy simulation program), and creating instances of the slave programs (using an instantiation approach) at every time step of these master program to exchange information. An approach like this has a fundamental limitation in modeling the adaptation of a system and are explained in the subsequent chapters of this dissertation. Overall, all the above-mentioned frameworks have several limitations which dent the possibility of seamless representation of the effects of energy influencing factors, and inter dependency of various energy needs in a building.

In summary, the life cycle based studies perform cumulative based quantification of building's energy use in its life cycle, whereas the co-simulation based approaches analyze the energy use and the effects of dynamic building parameters for a shorter span of time. The overall objective of both these type of studies is to understand building's energy use better, and develop energy savings strategies. But currently, both these are lying in separate domains. Therefore, the major limitation of the existing energy analysis methods is that both these approaches are being developed separately with very less connections. Given the fact that energy predictions using the current simulation approaches often deviate by 30%-100% when compared with the actual energy use (Yudelson 2010, Turner and Frankel 2008, Dell'Isola and Kirk 2003, Soebarto and Williamson 2001), the real need is for a framework that incorporate the dynamism in a building's entire life cycle into consideration.

1.3 Problem statement

Even though the life cycle based and the co-simulation based approaches outlined above have provided advances to the building energy monitoring domain, there are many limitations that need to be addressed effectively. The energy consumption of a building is highly dynamic and depends upon various parameters that continuously affect the building performance during the entire life span. To analyze these factors, the coupling system needs to emulate the effects of several factors occurring during the entire life cycle of a building. For achieving this, the simulation frameworks should adopt a systems approach and need to facilitate easy message exchange features across simulators that model different components in the building energy analysis domain. To summarize, the main barriers that exist in the energy behavior of building are,

1. **Lack of flexibility in the existing co-simulation schemes**

   Accurate ways of measuring and monitoring the energy use in the use and maintenance phase of a building is extremely important because this phase consumes the maximum energy, and therefore provides maximum avenues in adopting energy efficient techniques. However, the energy simulation tools assume static parameters which does not mimic the dynamic behavior of building systems and the occupants. Even though several co-simulation frameworks are developed to address this, the available schemes also have several limitations. It does not allow a designer to incorporate a simulation model of their choice, which dents the chance of reusing existing simulators. In addition, the current schemes adopt an instantiating approach which does not allow the modelers to represent the overall systems adaptation effectively. Finally, the existing schemes in the building energy analysis domain does not provide viable options for programs and models to run on distributed workstations while exchanging information within each other.

2. **Lack of a systems approach in the life cycle based energy estimation**

   The energy requirements in a building's life cycle need to be analyzed by considering systems approach to capture the important relationships existing between the different energy requirements. Current mechanisms only consider the life cycle end cumulative values of energy requirements, and derive conclusions based on that. However, this approach is missing the effects of dynamic events such as the building performance degradation and material maintenance during the use and maintenance phase. The ideal way should be to visualize the effects of inter-relationships between different energy related actions in a building's life cycle, thereby providing options for adopting better energy saving strategies.

3. **The need for a life cycle energy simulation mechanism**

   The life cycle energy analysis domain and the energy based co-simulation frameworks are moving in relatively different tracks, and there is a need for a strong mechanism that integrates both. Such a framework only can represent the true dynamic behavior of a building over its entire life cycle.

Addressing these barriers will result in a fully integrated building energy management infrastructure that help the facility managers and other building stakeholders to take full advantage of the fundamental process level simulation tools and components. This demand coupling several modules that represent the various diversities in a building, and therefore the need is for a framework that can perform a coupled simulation across distributed workstations that model the effect of specific factors (e.g., varying building performance, occupant behavior). It is a significant challenge to combine these results together to estimate the total integrated life cycle energy performance of a building by accounting for all the factors. However, the general objective of this dissertation is to develop a basic framework that performs a life cycle based energy simulation framework by coupling with individual simulators, and demonstrate the usability of such a scheme using several case studies. This proposed framework will provide a new direction towards visualizing and analyzing the total life cycle energy use in a building, when subjected to several dynamic factors.

1.4 Dissertation organization

The current chapter has outlined the importance of doing this research. Chapter-2 is focused on a thorough analysis on the existing literature, and discuss the motivation for doing this research. Subsequently, the main objectives of this dissertation are outlined which is followed by establishing the methodology adopted. Chapter-3 describes the need of a flexible coupling mechanism in the building energy analysis domain. Chapter-4 develops a coupled system of two simulation models (an energy simulation model and an occupant behavior model) to analyze the effects of energy based interventions on the occupant's behavior and the energy consumption. Chapter-5 generalizes the above coupling scheme by developing an innovative distributed co-simulation mechanism, LABS (Lightweight Adaptive Building Simulation) framework, and demonstrate its applicability using a case study involving occupant's thermal comfort behavior. Chapter-6 adopts a system dynamics approach to analyze the effects of material performance variations on building's life cycle energy consumption. Chapter-7 integrates the building performance simulator (as developed in Chapter-6) with the occupant behavior simulator (as developed in Chapter-5) to result in an integrated life cycle based building energy simulator. Chapter-8 summarizes the several verification and validation techniques commonly adopted in the simulation domain along with describing the methods adopted for the models developed in this dissertation. Chapter-9 discusses the major findings from this research and concludes with the final remarks.

CHAPTER 2

Literature Review and Research Objectives

2.1 Summary

As briefly introduced in the last chapter, the current energy analysis measures are centered on two approaches. The first approach quantified the energy requirements over the building's entire life cycle, by adopting LCA based methodologies and using the energy simulation tools. Meanwhile, the second approach exclusively developed co-simulation frameworks to incorporate the effects of several dynamic factors in static energy simulation. The initial two sections of this chapter discuss more details of these approaches, along with their limitations. Subsequently, the key research gap is discussed, followed by establishing the objectives and the methodology of this dissertation.

2.2 Estimating energy consumption in buildings - A life cycle approach

The energy needs in a building are spread out across its several life cycle phases such as the material manufacturing and construction phase, use and maintenance phase, and the end of life phase (Bayer et al. 2010). In conventional buildings, the material manufacturing and the construction phase generally account for around 20% of the total energy requirements, and the remaining 80% of the energy requirements occur in the use and maintenance phase (CSSBI 2013, UNEP 2007). However, in the case of low energy buildings, the energy requirements in the material manufacturing and construction phase account up to 40-60% of the total energy requirement because of the high performing materials and systems being used in it (Thormark 2006). One advantage of such a building comes in terms of lesser energy required during the use and maintenance phase due to higher overall building performance (Hernandez and Kenny 2010). The end of life phase includes the energy required for the building demolition, and the energy that can be recovered through material recycling (Dixit et al. 2010, Thormark 2006, 2002). The energy requirements in all these phases can be generally categorized into embodied energy and operating energy, and the estimation procedures of these are discussed in detail in the below sections.

2.2.1 Embodied energy (EE)

The term *"Embodied Energy"* is subject to various interpretations by different authors (Miller 2001). In general, EE in buildings can be defined as the energy expended for material production, building construction and operation, and final demolition and disposal. There are two components of EE, such as the direct energy and the indirect energy. Direct energy refers to the "energy involved in various onsite and offsite operations, such as prefabrication, assembly, transportation and administration", and the indirect energy includes the energy incurred during the various life cycle phases such as the Initial Embodied Energy (IEE), Recurrent Embodied Energy (REE) and the Demolition Energy (Dixit et al. 2012, 2010). IEE is the energy expended for material production and the building construction (Bayer et al. 2010, Dixit et al. 2010, Cole and Kernan 1996). Recurrent Embodied Energy (REE) is the energy spent for carrying out regular maintenance and replacement activities of materials to maintain the performance of the building at satisfactory levels (Crawford et al. 2010, Treloar et al. 2000, Cole and Kernan 1996). Demolition energy accounts for the energy required for demolishing and disposing of the building materials (Dixit et al. 2010). The end-of-life phase also includes the embodied energy that can be recovered by means of reusing some of the materials (Thormark 2006, 2002).

These EE requirements are generally estimated with the help of life cycle analysis (LCA) based databases (e.g., ATHENA Impact Estimator V4.2 2013, Building's Energy Data Book U.S DOE 2012, BEES 2010, ICE Database). Life Cycle Assessment (LCA) is an established analytical method for assessing the energy requirements and environmental balance of a product, process or service (Horvath 2004). For manufacturing any product, there are several processes in the supply chain, which directly or indirectly contribute towards the final product. LCA systematically analyses the energy requirements and associated environmental impacts of all these processes in a systematic manner. Hence through the LCA approach, various EE databases provide the energy required for producing a unit quantity of a material, normally expressed in MJ/ kg (Dixit et al. 2010) that can be used for estimating the total EE in a building. For instance, the 'ICE database' provided the EE intensity of more than 200 common building materials, and the coefficients for calculating the embodied carbon equivalent (Hammond and Jones 2008). These EE intensity values can be used for estimating the total EE requirements in the building.

2.2.2 Operating energy (OE)

While EE represents the energy embodied in a building, the OE represents the energy needed for operating the various building systems and services. The OE is generally estimated with the help of energy simulation tools that takes building details as input and generate energy consumption estimates based on the input parameters. There are several such tools (Maile et al. 2007 and Crawley et al. 2008) that provide options for performing an energy simulation, and the major ones are summarized in

Table 2-1 below. An energy simulation program takes inputs about a building such as the location, building shape, weather details, envelope material properties, internal gains from equipment, lighting and occupants, cooling and ventilation systems, and details about heating, to name a few. Based on these model inputs, a typical simulation run provide the energy requirements for building heating, cooling and lighting, and many other detailed information such as the water consumption pattern and comfort related parameters.

Table 2-1 Energy Simulation tools and its capabilities

Sl. No	Name of simulation program	Major capabilities
1	Building Loads Analysis and System Thermodynamics (BLAST), Version 3.0 Level 334	Predicting energy consumption, energy system performance and cost
2	BSim, Version 4.4.12.11	For energy design of buildings and for moisture analysis
3	Designer's simulation toolkits (DeST) Version 2.0	Analysis of building thermal processes and HVAC system performance
4	DOE-2.1E Version 121	Predicting hourly energy use and energy cost of a building
5	ECOTECT Version 5.50	Architectural design and analysis tools with a wide range of building energy performance analysis functions
6	Energy-10 Version 1.8	Full life cycle costing and energy analysis software
7	eQUEST Version 3.55	Building energy use analysis tools with easy visualization
8	ESP-r Version 10.1	General purpose, multi-domain—building thermal and energy analysis tools
9	IES /Virtual Environment	Detailed energy simulation tool with inter-operability features with building modeling tools
10	TRACE 700 Version 4.1.10	Design, System, Equipment and Economics
11	TRNSYS Version 16.0.37,	Transient system simulation program with a modular structure
12	EnergyPlus 8.5	Whole building energy simulation program that model energy consumption and water use in buildings.

Figure 2-1 below shows screen shots compiled from an *eQuest* energy simulation analysis, for a two-story office building. The left-hand side denotes one input sheet of *eQuest* with building occupancy schedule information. *eQuest* provide options for incorporating several pages like this to input the information about building footprint, envelope details, building interior constructions, and HVAC specifics. These input pages can be used to model the building's features as close as possible. The right-hand side of the figure shows the electricity and gas use requirements distributed across the various end use categories. It can be seen from the figure that, the energy use heads that are directly related to the occupants, such as space heating, space cooling, water heating and lighting is accounting for close to 70% of a typical building's consumption (DOE 2012). Therefore, it is very important to have mechanisms to analyze the dynamism in occupant's energy use patterns and its influence on the total OE requirements in the building.

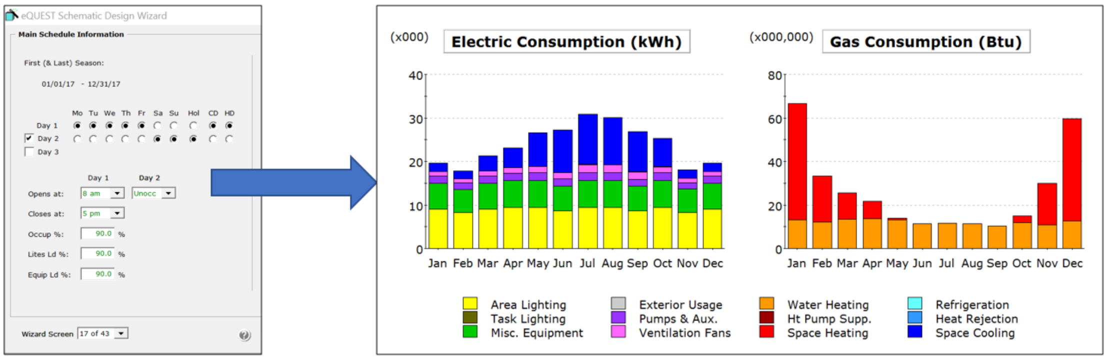

Figure 2-1 eQuest input screen and the energy simulation results

2.2.3 Measuring EE and OE for life cycle energy estimation

The EE databases and the OE estimation tools described above are widely used for estimating the life cycle energy requirements in buildings. Even though building energy dominance is during the use and maintenance phase, the importance of embedded materials and its maintenance also needs to be given equal importance. Therefore, several studies used the EE databases and designed schemes to choose sustainable material options. For instance, embodied energy of argon, krypton and xenon cavity filled windows were quantified, and found out that argon filled cavity windows involve the least quantity of embodied energy and produce minimal amounts of greenhouse gases (Weir and Muneer 1998). Similarly, a carbon footprint monitoring tool developed using ICE database predicted the visual impact of sustainability in construction activities by means of color coding, and projected the environmental impacts of various construction activities (Memarzadeh and Golparvar-Fard

2012). Likewise, an impact allocation and reduction scheme providing embodied impacts of materials was developed to help the designer to select environment-friendly building materials for designing sustainable buildings (Basbagilla et al. 2013). The *LCADesign* developed by the Cooperative Research Center for Construction Innovation in Australia was also a step in this direction, which estimated the resource use and environmental emissions of several building materials and design choices (Seo et al. 2007). Meanwhile, Russel-Smith and Lepech (2011) developed a computational framework that estimated the environmental impacts of different building construction materials, and allocated these impacts to different activities in the project execution schedules.

Another set of studies coupled the EE databases with the building modeling tools to generate energy efficient building design options. A revit-integrated *RTEI*™ tool was developed for estimating the environmental impact of building materials to help the building designers in design optioning and iteration (Bates et al. 2013). Similarly, Wang et al. (2005) developed a multi-objective optimization model for the initial design phase of a building, which can be used to locate optimum or near optimum green building designs through the multiple Pareto solutions. Shiftehfar et al. (2010) similarly expressed the embodied carbon emissions of a various building design options in terms of the equivalent number of trees to be planted, which can be used as a measure for comparing various design options. All these studies developed frameworks that coupled and analyzed different material choices and design options, thereby resulting options for creating more sustainable and energy efficient building design. But the major focus and the applicability of most of these frameworks were limited only to the building design phase.

Even though the initial material and design choices are critical to achieve energy efficiency, the EE requirements during the use and maintenance phase also is found to be equally important. Cole and Kernan (1996) studied the significance of REE in a case study building in Canada and suggested that it can reach up to 1.3, 3.2, and 7.3 times the IEE for a lifespan of 35, 50 and 100 years respectively. Another study by (Treloar et al. 2000) found out that REE can reach up to 32% of IEE over a period of 30 years. Similarly, a study of a residential building in Australia estimated that REE can reach up to 67% of IEE over a 50-year service life, and 150% over a service life of 100 years. (Fay et al. 2000). Another study by Crawford et al. (2010) suggested that the REE in a building could vary from 7% to 100% of IEE. Even though the REE share obtained across these studies varied, all of them established the fact that REE can be as significant along with the IEE.

EE associated with the end-of-life phase has been omitted by numerous studies citing that it is likely insignificant when a building's entire life cycle is considered (Crawford et al. 2010, Crowther 1999, Suzuki 1998). At the same time, it is also found out that the environmental emissions associated with the demolition activities can reach up to 8% of the total life cycle emissions for a building (Vieira and Horvath 2008). Furthermore, the most important aspect during this phase is being able to estimate the energy that can be recycled back through reuse of materials. The recycling potential from a normal building during the end-of-life phase is estimated to be around 12% of the energy used for material production. Meanwhile for a HPB, material recycling is expected to provide around 37- 42 % of the IEE back into the grid (Thormark 2006, 2002). This energy from recycling is significant because it reduces the total life cycle energy requirements in the building.

So far, the discussion has been mainly on studies that measured the EE, and its comparison with the OE requirements. Currently, the approach adopted in estimating the life cycle OE is by estimating the annual OE using the energy simulation tools, and then estimating the cumulative OE for the analysis period. For instance, Treloar et al. (2000) calculated the annual OE of an Australian building by using an energy simulation software, *CHEENATH*, and the 30-year life cycle OE is calculated by multiplying the annual OE with the total analysis period. A similar approach is adopted by Aye et al. (2012) to estimate the life cycle OE using the *TRNSYS* simulation software. Likewise, Fay et al. 2000 also calculated the annual OE using the simulation software, *NatHERS* to estimate the annual OE and then the life cycle OE. Similar approach is adopted in Rauf et al. 2013 and Crawford et al. 2010. In general, life cycle EE is estimated using the LCA based databases and life cycle OE is found out using the energy simulation tools.

In summary, the general methodology adopted so far is to estimate the energy requirements by using a cumulative based approach. Even though these mechanisms have delivered several insights about the importance of each energy requirements in a building, there are several limitations that needs to be addressed. It is also opinioned that the results vary across different studies mainly because of the use of different EE databases, methodological inconsistencies and assumptions, and the regional and technological variations (Gursel et al. 2014). In the following sections, the major limitations of the existing life cycle based energy estimation approaches are described.

2.2.4 Limitations of life cycle based energy estimating approaches

The major limitations of the life current measuring approaches are with respect to considering fixed life cycle analysis period, fixed material replacement rates for REE estimation, and the cumulative based estimation of OE requirements over the life cycle. In addition, most of the studies are limited only to the building design and construction phases. These limitations are explained below in detail.

Almost all the studies in this domain considered a fixed time frame (e.g., 35 years, 50 years, 100 years) for performing the total life cycle energy and environmental emission analysis. However, this considerably limits the applicability of those studies since the result obtained for a typical building with a shorter lifetime need not be true for a building that is constructed by keeping a longer lifetime in mind. Normally, the life expectancy of buildings varies depending upon the purpose. Thus, there is a real need for a generalized model that can be applied to analyze the life cycle energy requirements for any building with any expected lifetime. Similarly, estimating the REE by considering a fixed replacement period for the materials does not depict the real building life cycle scenario. The maintenance and repair activities performed on a building can significantly extend the service life of building materials (Grant et al. 2014, Matulionis and Freitag 1991). But, most of the studies have arbitrarily assumed the service life for various building materials (Grant et al. 2014, Mora et al. 2011) because of a lack of data regarding the service life of different building materials (Rauf and Crawford 2014).

Another limitation in this domain is that the studies have majorly focused on performing a cumulative based analysis for estimating the EE and OE related requirements. Otherwise stated, the current focus of life cycle based analysis is in estimating how much would be the total EE and the OE at the end of the life cycle, and drawing comparisons and inferences based on that. Analyzing EE or OE in isolation like this will not provide enough conclusion as the EE decision will have an impact on the OE decision. Therefore, the current approach does not incorporate the energy effects of varying performance levels of building materials and systems, occupant behavior patterns, effect of climate changes at a building operation level, and varying building operation policies. Incorporating the effects of such diversities is a must in this domain as these diversities are one strong reason for the actual energy use to deviate from the predicted. In the literature, there are attempts to model some of these diversities and applicability of those are limited to analyzing the energy use pattern for maximum a year period. The main theme of these approaches lies in coupling several simulation modules to analyze the effects of several dynamic factors, and are discussed in detail below.

2.3 Coupled simulation approaches in the building energy analysis

The last few decades have witnessed a paradigm shift towards creating interoperable and composable simulation frameworks that can analyze a complex system effectively, when compared to independent and standalone simulation models (Page 2007). These frameworks also facilitate reuse of existing models thereby avoiding the need for creating separate tools for each purpose (Dubitzky et al. 2012). Two terms that are often used to describe these models are co-simulation and distributed simulation. A co-simulation refers to a framework in which at least two simulators, are coupled to exchange data while its runtime (Becker 1992), not necessarily in distributed work stations. Meanwhile, a distributed simulation refers to simulation programs interacting and exchanging information across models, running in several computing platforms connected by a local network or a globally distributed network (Fujimoto 2015). The goal of both these methods is to create an interconnected or coupled system that can solve a problem by allowing two standalone simulation models to mutually exchange information. Studies have also combined both these methods to develop distributed co-simulation frameworks wherein simulation models co-simulate across distributed work stations, during the runtime (Sadjina 2017, Kim et al. 2002, De Mello et al. 2002, Hessel et al. 1999).

The Defense Advanced Research Projects Agency (DARPA) sponsored project SIMNET (SIMulator NETworking) during the 1980's was one major distributed simulation project (Page 2007) that kick started many such projects in the manufacturing, automotive and robotics industry. Some of the main frameworks developed are High-Level Architecture (HLA) (Kuhl et al. 1999), Functional Mockup Interface (FMI) (MODELISAR 2008-2012), and Lightweight Communications and Marshalling (LCM) (Huang et al. 2010). HLA has been widely used to develop distributed simulation systems in the defense area, manufacturing, offshore oil production process, and for simulating processes in the medical domain (Moller 2013). Meanwhile, FMI is a tool independent standard used for co-simulation of various dynamic models, and is widely used to develop control mechanisms in aerospace systems, manufacturing and automotive industry (MODELISAR 2008-2012). LCM is a recent entry into this domain, which use a set of libraries and tools to support inter-process communication mechanisms required for developing robotics systems (Huang et al. 2010).

In the building energy analysis domain also, there is a growing need for performing coupled simulation. Because, traditional energy simulation tools assume static or pre-defined schedules and parameters to estimate the behavior of the building systems, which does not accurately mimic the actual dynamics during a building's real time operation (Thomas et al. 2016a, c; Hong et al. 2015a; Azar and Menassa 2015; Thomas et al. 2015a, b; Langevin et al. 2014; Zhao et al. 2014; Wetter 2011; Bourgeois et al. 2006). The Annex 53 of International Energy Agency has noted that there is a wide variation among researchers in representing the factors that influence the building's energy consumption, and has come up with a generalized category of factors as shown in Figure 2-2 below.

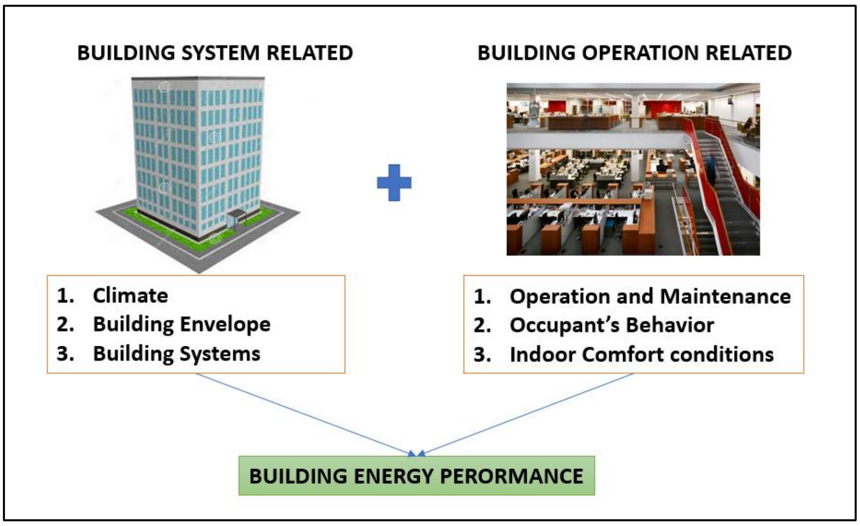

Figure 2-2 Factors influencing the building energy consumption (Adapted from IEA 2013)

In general, there are building related factors and occupant related factors that bring dynamism to a building's energy consumption scenario (IEA 2013). In the below sections, these two categories are discussed with a specific focus on the occupancy related factors.

2.3.1 Building performance related factors and its effects on the energy consumption

The performance of building materials and systems along with the climatic conditions, influences the energy consumption in the building. Mainly these factors influence the heating, cooling and the ventilation requirements in a building (IEA 2013). Table 2-2 below summarizes some of the major factors and the energy related components these factors could influence.

Table 2-2 Building material and systems properties and its energy effects

Factor	Space Heating and Cooling	Ventilation
Climate	Cooling degree days, heating degree days, wind velocity and direction, humidity	Heating degree days, wind velocity and direction, humidity
Building Envelope	K-Value, material composition, Solar heat gain coefficient, air tightness, fenestration properties, thermal characteristics	Air tightness
Building Energy Systems	Air Conditioner properties, dehumidifier parameters, HVAC system properties and efficiency	Ventilation systems, economizers, air distribution systems

Regarding the building performance related factors, this dissertation has focused only on the thermal characteristics of the building envelope (e.g., R-Value), and its influence on the building's life cycle energy consumption. This is analyzed and discussed in detail in Chapter-6, which focused on understanding the effects of external envelope degradation on the energy requirements in a building. The effects of other factors as mentioned in Table 2-2 above are not a primary focus of this dissertation, and are therefore not considered for further analysis. In the section below, occupant's energy use and thermal comfort behavioral patterns and its effects on energy consumption are discussed in detail.

2.3.2 Occupant's energy use behavior and its influence on the energy use in buildings

Broadly, occupant's energy use behavior can be divided into two types; active and passive (Mahdavi 2011). Active refers to the effect of direct actions of the occupants (e.g., switching lights on and off, adjusting the thermostat set points, opening the window shades) on the energy use in the building. Meanwhile, passive denotes the effects caused due to the mere presence of people (e.g., internal heat gain from people). There are several attempts to model these dynamic behavioral patterns by adopting different methodologies, behavioral factors and varied building locations. These efforts are categorized and discussed in detail below.

Generally, there are two purposes for modeling the occupant behavior in buildings: 1) to understand the driving forces in the behavior itself, and 2) to model the impact of various dynamic occupant behavior on building's energy use. Based on the methodology adopted, these models can be mainly categorized into psychological models, average value models, deterministic models, probabilistic models, agent-based models and action-based models (IEA 2013). Psychological models studied the several factors that determine the behavioral traits of people (Klöckner 2004, Icek 1991, Fazio 1990, Van Raaij et al. 1982). Average value models used various methods such as cluster analysis, crowd source inventory database, genetic algorithm, random numbers, and combination of simulation results to portray the effect of random occupant behavior on the energy use of a building (Zhao et al. 2012, Azar and Menassa 2012). Meanwhile, deterministic models studied human activities by means of pre-defined schedules and rules (Glicksman 1997). In the probabilistic modeling approach, a probabilistic distribution is preferred for the behavioral trait instead of the static pattern as adopted in the deterministic model. Meanwhile, agent based modelling (ABM) followed a bottom-up approach that dealt with agents' behavior and interactions at a micro level and its influence on the macro level (energy consumption within the building). Action based modeling studied the movement and control actions of occupants in addition to the behavior patterns (IEA 2013).

More recently, Li et al. 2016 presented the MOA (Motivation, Opportunity and Ability) framework to better define the drivers and actions of occupant's energy use behavior. Similarly, Hong et al. (2015a) proposed a DNA ontology suggesting a Drivers-Need-Action framework to explain the occupants' energy use levels. Another set of studies in this domain concentrated on the effects of various occupancy-based interventions (educational programs, peer pressure, energy use feedback) on the energy use behavior/intensity (e.g., moderate, extreme) patterns of the occupants (Azar and Menassa 2015, 2014, 2012). Overall, all the above-mentioned approaches established that different occupant behavior traits and various occupancy based interventions can significantly influence the energy consumption patterns in a building.

2.3.2.1 Need for analyzing the thermal comfort of occupants

In addition to analyzing the energy effects of occupant's energy use behavior, another crucial factor to be considered in tandem is occupant's comfort in closed building environments. It is important because people spend around 92% of their time in closed building environments, and the energy saving efforts should not be at the expense of compromising occupant's comfort levels in the building (Klepeis et al. 2001, Neil 2001). Several studies developed frameworks that is based on Predicted mean vote (PMV) concept which is the most preferred index for measuring the thermal in indoor living environments (Ku et al. 2015, Fabbri 2015). PMV was originally developed by Fanger (1970) by analyzing the comfort levels of occupants in closed climate chambers.

PMV concept considers six factors that define the thermal sensation of occupants in a building, such as occupant's metabolic rate and clothing insulation, air temperature, mean radiant temperature, air velocity, and humidity. Figure 2-3 below shows the predicted mean vote estimation factors and the range used for measuring the PMV levels of an occupant. Based on these factors, Fanger (1970) developed equations that output a numerical value within *-3* to *+3* range, which defined the thermal sensation level of a building occupant. A value of *'0'* for PMV indicates that the occupant has no discomfort, while other values within the above-mentioned range indicates increasing levels of discomfort. Olesen (2004) summarized the adaptation of PMV index across various national as well as international codes, and among those, ASHRAE standard 55 and ISO 7730 are the most referred standards that provide details on how to measure the PMV levels of building occupants. Another index which is calculated as a function of PMV is the Predicted Percentage of Dissatisfied (PPD) which predicts the percentage of occupants who will be dissatisfied with the thermal conditions. As PMV moves further from the zero mark, the PPD also increases, and as per ASHRAE Standard 55, the recommended and accepted PPD range for thermal comfort is less than 10% persons dissatisfied in an interior space.

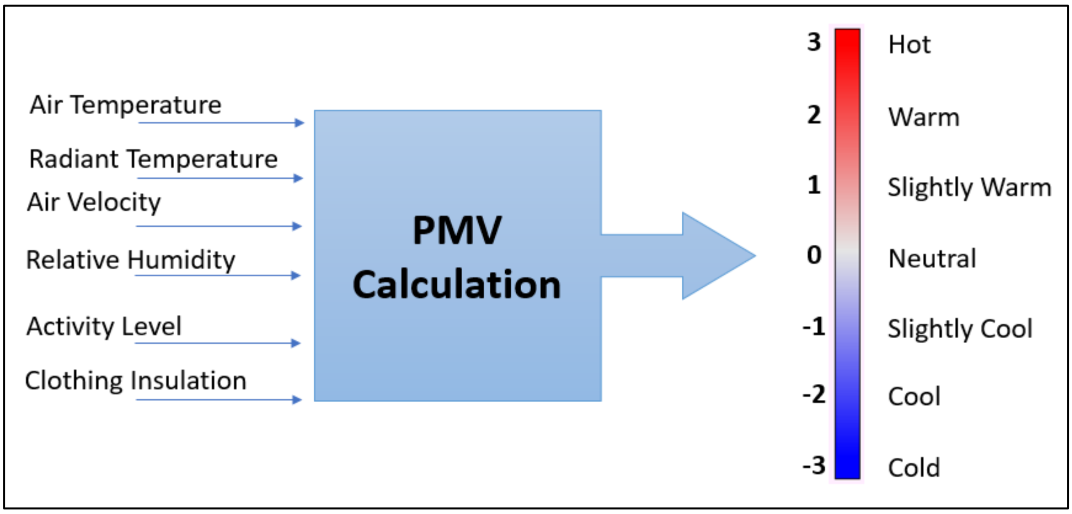

Figure 2-3 Predicted Mean Vote and thermal sensations

Even though the PMV index works well with climate controlled spaces, its accuracy reduces with naturally ventilated spaces (Yang et al. 2014), and this has resulted in improved versions of the PMV index that can be categorized in general, as adaptive thermal comfort models. These models are based on the adaptive principle, which can be defined as; "If a change occurs such as to produce discomfort, people react in ways which tend to restore their comfort" (Fabbri 2015, Nicol and Humphreys 2012). Some of the adaptive behavioral patterns analyzed by studies include, but are not limited to, opening or closing the windows, adjusting the window shades, controlling the fan or heater speed, adjusting the thermostat temperature, and the lighting appliance use. In general, it has been opined that occupants adjust themselves to achieve thermal comfort, and by analyzing the dynamic pattern of a suitable thermal comfort index, building control actions can be optimized by the facility managers. In addition to these efforts, some studies have also quantified the energy saving possibilities of the adaptive behavioral patterns of building occupants, by controlling and influencing various energy intensive actions (Kim et al. 2015, Daum et al. 2011, Alcalá et al. 2005).

The common methodology adopted for developing any thermal comfort based model includes collecting relevant data for calculating the PMV index through questionnaires, sensors and building energy management systems, and using this data to develop the model. Calvino et al. (2004) used a fuzzy based logic to vary the PMV of occupants from a discomfort zone to a comfort zone by optimizing the speed of the heating fan. This study showed that by controlling the PMV, the HVAC related equipment in the building could be optimized. Similarly, Haldi and Robinson (2010) collected data on building occupants' comfort parameters through sensors and electronic surveys, and found out the probability distribution for the adaptive thermal sensation ranges. Subsequently, this study established the relationship between occupants' actions and its interplay with the thermal sensation levels. The case study results included an adaptive model for the prediction of actions on windows, visual sensation and comfort.

Daum et al. 2011 also prepared a probabilistic distribution for the thermal sensation level, and an adaptive control model based on collected data for representing the effect of window shade action. Likewise, Ku et al 2015 developed an inverse PMV model calculating the temperature settings of air conditioners based on fuzzy control logic. Three scenarios were considered and the energy savings were recorded. Meanwhile, Kim et al. (2015) proposed alternate aPMV and nPMV models to express the thermal comfort of the building occupants, and suggested that adaptive PMVs are better compared to the original PMV model. In summary, adaptive thermal comfort models provide an opportunity for establishing how adaptive behavior of occupants can be used for optimizing building energy intensive systems (for e.g., air conditioner system) thereby maximizing the energy savings.

Therefore, it is imminent that any energy simulation analysis should have options to incorporate the occupant's energy use behavior, building's varying performance conditions and occupant's comfort preferences into consideration. As was previously mentioned, existing energy simulation programs assume static occupant behavior patterns and energy use behavior while estimating the energy requirements (Hong et al. 2015a, Azar and Menassa 2015, 2014, 2012, Menassa et al. 2014, IES VE 2014, DOE-2.3 2014, EnergyPlus 2013, Oreszczyn and Lowe 2010, eQuest 2010). In actual practice, this approach has its own drawback as the occupancy profiles or energy use behavior and their comfort preferences within a building need not always follow the same pattern. Studies have adopted a co-simulation based approach to address this problem by enabling message exchange between energy simulation and simulation modules that model the dynamic behavioral patterns in the buildings.

2.3.3 Co-Simulation frameworks focusing on occupancy behavior

As was previously mentioned, there are several factors that bring dynamism to a building's performance. The overall idea adopted in the co-simulation frameworks is to model and incorporate the dynamic effects of these factors in energy simulation. Some of those factors are shown in Figure 2-4 below. At the occupant level, there are several activities such as opening or closing the windows, adjusting thermostat levels, interactions with the various equipment and lighting systems. Similarly, at a building level there can be energy based intervention programs, fluctuating building system performance and varying occupancy levels. For instance, Langevin et al. (2014) used MATLAB to model occupant's window opening/closing behavior, use of heaters/fans and thermostat set point adjustments, and used BCVTB to represent the effects of these behavioral variation patterns in an energy simulation. Similarly, Nouidui et al. (2014) used the FMU scheme to couple an HVAC (Heating Ventilation and Air Conditioning) module that simulated the variations in sensible and latent heat gain in a room with an energy simulation analysis to represent its energy effects.

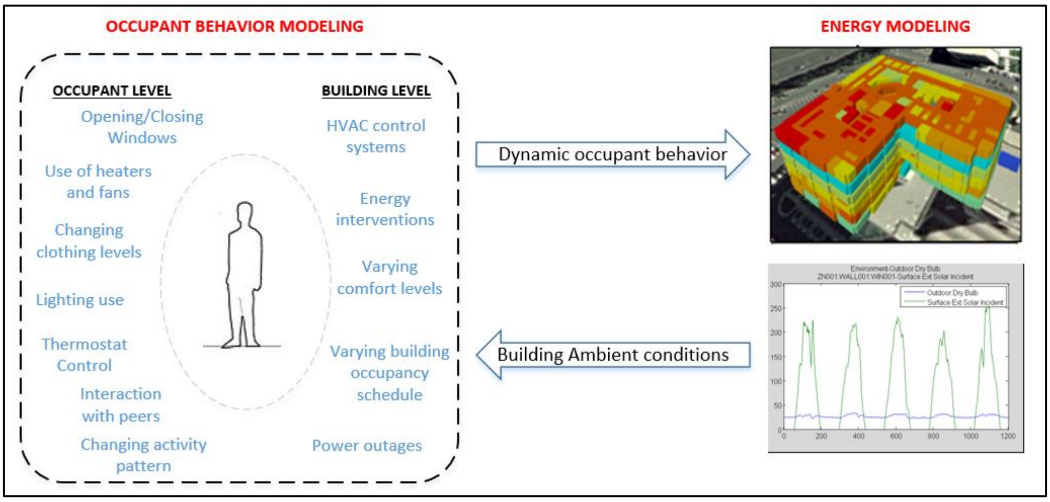

Figure 2-4 Basic idea of co-simulation frameworks in the building energy domain

The attempts to create co-simulation frameworks in the building energy analysis domain started only about a decade ago. Bourgeois et al. (2006) incorporated a sub hourly occupant control model into the energy simulation of a single room office building. In this framework, the occupancy model exchanged the stochastically derived occupancy profiles at every five-minute time step with the energy simulation program ESP-r to estimate the energy consumption. A similar framework using ESP-r was developed by Rijal et al. (2007) to study the effects of window opening behavior of occupants. In 2011, Wetter created the BCVTB framework, which was subsequently adopted by several studies. Duan and Dong (2014) used BCVTB to control the thermostats in a building based on real occupancy patterns. Likewise, Langevin et al. (2014) proposed a human and building interaction toolkit that coupled energy simulation with an agent based occupant behavior model using BCVTB.

Similarly, Menassa et al. (2013) used HLA, a coupling tool developed by Kuhl et al. (1999) based on the rules and specifications defined by Institute of Electrical and Electronics Engineers (IEEE-1516 2001), to couple an occupancy based agent based model with a DOE-2 (DOE 2017) energy simulation program. Another recent addition to this domain is the FMU proposed by Nouidui et al. (2014). The FMU scheme eliminated the need of a middleware to perform the co-simulation. Subsequently, several studies have adopted FMU framework to analyze energy related occupant behavior (Hong et al. 2015a, b), indoor air quality analysis (Chen et al. 2015), and adaptive solar energy building envelope systems (Novelli et al. 2015).

2.4 Limitations of existing approaches

Even though the existing mechanisms achieved the goal of modeling and analyzing the dynamism involved in a building's operation, there are two major limitations with the current schemes which are explained below in detail.

2.4.1 Complexity aspects of existing mechanisms

BCVTB and HLA are essentially middleware schemes that add an additional transaction layer between the interacting programs. In this procedure, each simulation program in the loop needs to have connection interfaces with the middleware. This increases the complexity of the co-simulation because of this extra layer (Nouidui 2014). When the number of connected components increases, this results in developing more such interfaces thus increasing the complexity of the overall process. To mitigate this complexity, the FMU-import framework removed the concept of middleware and introduced the option of allowing a standardized interface, FMI, where all the contributing programs and the master program abide to the rules of this standardized interface. This addresses the complexity issues associated with subscribing to a middleware.

Even though the FMI has coupling support for close to 34 programs, it is still an issue that how a simulation program outside this list can be brought into the coupling scheme. As was mentioned in the introduction, some of the common simulation platforms are yet to be supported by the FMU-import framework. Similarly, even though FMI has support for a specific programing interface, it does not mean that all the simulation programs developed in that interface can be readily extracted as an FMU. For instance, FMI provides *JavaFMI* which allows the modeler to package a java based program as an FMU to perform co-simulation. However, to do so, commercial java-based simulation software programs (e.g., Anylogic) need to possess mechanisms to convert a program as an FMU for co-simulation. As per the current scenario, if a modeler wants to use an existing simulation model developed in Anylogic into the FMU-import framework, this is not possible. The necessary features for Anylogic might be added in the future, but the current scheme of things always does not ensure support for incorporating a wide array of simulation programs thus limiting the possibility of existing code reuse.

Hence, even though FMI provides support for a specific programming interface (e.g., Java, python), it does not ensure that a software program created in that interface can be readily incorporated as an FMU. Instead, the proposed framework through this dissertation provides the option to directly couple any two given simulation models (using an ASCI file based data exchange), and perform co-simulation regardless of the programming environment the models are developed in. Such a system would allow the programs to interact freely thereby eliminating the need of middleware, and the need of checking the compatibility of the standardized framework rules.

2.4.2 Current instantiation approach and its limitations

The major motivation behind the BCVTB and FMU systems is to provide modularity (Wetter 2011). This allows the designer to model additional components of building energy and control systems (e.g., HVAC model or an occupant behavior model) separately, and couple it with the base energy simulation engine. Even though a direct implementation of all the equations in one simulator might be computationally efficient, such an implementation would be practically enormous and would be difficult to realize for an individual simulation project (Wetter 2011). This was a major motivation for creating BCVTB/FMU by creating several submodules that represent specific added features of a building system and couple it with the base energy simulation engine. In a BCVTB/FMU environment, the base energy simulation engine is termed as the master program, and the submodules are called as the slave programs. The communication between the master program and the slave programs occur at the time step of the master program. This means, at every time step of the master program, instances of the slave programs are created, variables are exchanged and the responses from the slave programs are received back at the master program for time integration (Nouidui et al. 2014; Wetter 2011). In addition, the FMU is terminated, at the end of a time step by freeing the corresponding memory (Nouidui et al. 2014). This is the typical procedure in the current co-simulation process and can be referred to as an *instantiation approach* as instances of slave programs are created at every time step of the master program.

This instantiation approach is very well suited to model deterministic events. For example, Nouidui et al. (2014) created a shading controller using Modelica (Modelica 2017), and packaged as an FMU for co-simulation with EnergyPlus. At every time step of

EnergyPlus, this FMU is actuated, the dry bulb temperature and the solar irradiation is exchanged to this FMU and upon receipt of this information, the FMU calculates the shading actuation signal for the next time step of EnergyPlus. Similarly, using Modelica, Wetter (2011) developed an air conditioning system and coupled it with the EnergyPlus simulation using BCVTB. The air conditioning system takes the air temperature and the water vapor concentration as input signals, and exchange the sensible and latent heat flow rates back to the EnergyPlus.

Even though coupling several such modules enhance the capabilities of an energy simulation program, it is not robust enough to model the collective adaptation and evolution occurring in the entire system. For example, using the BCVTB/FMU system, if it is required to couple an energy simulation program with an occupant behavior model that simulates occupants' behavioral adaptation over time, the only option is to exchange building related information at predefined time steps of energy simulation tool and get the response from the occupant behavior model at these time steps. However, in real time, occupants adapt to the evolving conditions in the building and this adaptation can occur at a different time step than the master program's time step. For instance, the peer pressure between the occupants (one occupant's behavioral pattern influencing the other one's behavior) occur continuously, and its varying effects needs to be captured efficiently.

Thus, a robust co-simulation framework in which all the slave programs runs in parallel with the master program, while exchanging the relevant information is required to model the adaptive components mentioned above. Such a system only can represent the adaptations occurring in every other component in the framework, and represent its effects on the energy consumption. The major difficulty in achieving such a scheme is managing the time synchronization across all programs as the run time mechanisms of individual programs vary widely. The proposed framework through this dissertation presents an innovative solution to achieve this time synchronization while also achieving the overall objective of distributed co-simulation (i.e., coupled simulation across remotely located workstations).

Therefore, the current approach requires a radical shift because in an ideal co-simulation network, programs might need to run in parallel exchanging information during each program's runtime. As was previously mentioned, occupants adapting their energy use behavior over a time step different than the master module also need to be accounted for. Similarly, the coupling framework must be simple to learn and implement and needs to have the flexibility to add simulation programs of a decision-maker's choice into the loop, thereby naturally promoting the reuse of existing codes and programs.

2.5 Key gaps identified

As mentioned above, the key gap identified from the current literature is the need for a distributed co-simulation approach in the building energy analysis domain. Figure 2-5 below depicts the different functional components involved in building energy analysis domain. Those are the building energy management system, various data collection mechanisms, energy simulation and optimization programs, dynamic behavioral and building performance variations, and unforeseen events and system failures. Incorporating the effects of these factors on a collective basis demands a framework that can work across distributed systems mutually exchanging information. Such a system only can help understand the building energy consumption mechanism better.

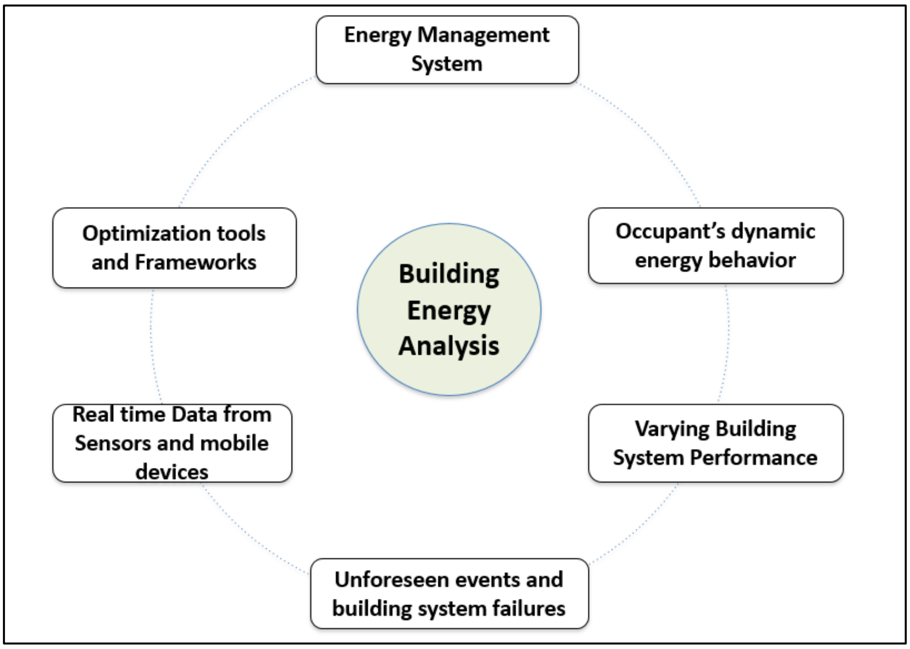

Figure 2-5 Building Energy Domain and need for a distributed analysis mechanism

The current co-simulation techniques in the building energy domain are highly complex and lacks the vigor and easiness in realizing this theme across distributed work stations. Thus, there is a strong need to simplify the co-simulation process in the building energy analysis domain, and give more importance to improving the fidelity and robustness of the individual components in the framework than the modalities of the connection mechanism itself. Realizing this scheme necessitates a systems approach to analyze the inter dependencies and feedbacks existing between different components in a building energy analysis domain. In addition to the systems approach, an agent based approach is also a necessity to model the energy simulation incorporating the dynamic behavioral patterns of building occupants.

Table 2-3 below summarizes the limitations of the existing frameworks, and the capabilities required for an ideal co-simulation framework. In general, the real need is for a framework in which all the contributing programs runs in parallel and mutually exchange the runtime variables. In addition, the ideal framework should have options for performing a distributed co-simulation and should easily be able to add a new simulation program into the loop.

Table 2-3 Key features and limitations of existing co-simulation frameworks

Functional requirements for co-simulation	BCVTB	MLE+	HLA	FMU	Remarks
Run-time variable exchange from EnergyPlus	YES	YES	NO	YES	This is a critical requirement as ambient building conditions need to be accessed during runtime.
Distributed Co-Simulation	NO	NO	NO	NO	This feature is required for connecting across different functional components.
Support to diverse simulation platforms	Limited	Limited	More support Available	More support Available	The ideal scheme should have options to incorporate any simulation program into the loop.
All simulation programs running in parallel	NO	NO	YES	NO	All simulation programs need to run in parallel to represent the evolution within the system.

2.6 Research objectives

The primary aim of this dissertation is therefore to develop a framework that can analyze the effects of several factors on the energy requirements in a building's life cycle, by utilizing a distributed co-simulation approach. Such a framework will have the capability to represent the inter-relationships existing between several factors, thereby providing guidance for better operation and maintenance schemes.

The main three objectives of this dissertation can thus be summarized as below.

1. To what extent can a lightweight communication mechanism be robust enough to support the development of the proposed distributed co-simulation scheme?
    a. The existing co-simulation frameworks in the building energy analysis domain lack the flexibility to connect across distributed work stations. The proposed framework through this dissertation would be an apt solution to address this problem, by enabling message exchange between remotely located work-stations running simulation modules of different origins.

b. The new flexible framework would allow the simulation modeler to introduce simulation tools of several programing platforms into the loop, which will promote reuse of existing models.

2. To what extent can a systems approach be used to study the effect of dynamic building performance on buildings' life cycle energy requirements?
   a. This framework plans to bring all the energy requirements in a building's life cycle to the same platform and visualize the effects of building performance related events on the energy use.
   b. A building owner can utilize this framework to weigh the impact of various energy related decisions (e.g., maintenance frequency of building materials and systems) to optimize the life cycle energy consumption of a building.
3. To what extent can a life cycle based energy simulation mechanism be created by utilizing the capabilities of the new distributed co-simulation framework?
   a. This framework aims to develop a grand coupled scheme that will combine the simulators created through objective-1 and objective-2.
   b. This framework will have the capability to represent the effects of several dynamic actions occurring during the entire life cycle of a building.

2.7 Research methodology

The methodology for this study includes several distinct phases, as illustrated by the flowchart in Figure 2-6 below. Each phase is later detailed in a separate chapter of this dissertation (e.g., Phase I-a in Chapter-3). It is also important to note that the work in these chapters has been published in several journal and conference papers, confirming the relevance and uniqueness of the various stages of this work. The following is an overview of the main phases as shown in Figure 2-6.

The Phase-I in general developed coupling frameworks to analyze the effects of dynamic factors that affect the energy use in a building's operation. Phase-Ia investigated the limitations of existing co-simulation schemes and proposed a new distributed co-simulation scheme using Lightweight Communications and Marshalling (LCM) to analyze the effects of occupant's dynamic energy related behavior. Phase-Ib realized this scheme by coupling an occupant behavior model and an energy simulation model. The occupant behavior model used an agent-based modeling concept and is a case study application of an OBM developed by Azar and Menassa (2015, 2014). Phase-Ic addressed the limitations of the existing co-simulation based schemes, developed a generalized distributed so-simulation scheme, Lightweight Adaptive Building Simulation (LABS) framework, and performed a case study to validate and demonstrate the usability of this new framework.

The Phase-II in general introduce a life cycle energy monitoring perspective to the building energy analysis and analyze the effects of building performance on the energy consumption. A comprehensive system dynamics model that analyzed the inter-relationships and feedbacks existing in building's life cycle is created through this phase. This simulator gather user's feedback about building operation scenarios and simulates the corresponding energy effects of those scenarios. This phase therefore use the system dynamics ideology to perform a dynamic life cycle energy estimation in a case study building.

The Phase-III use the LABS framework developed through Phase-I to couple the simulators developed through Phase-I and Phase-II. This simulator performs a life cycle energy analysis by incorporating the effects of several factors that influence the energy use in a building's life cycle.

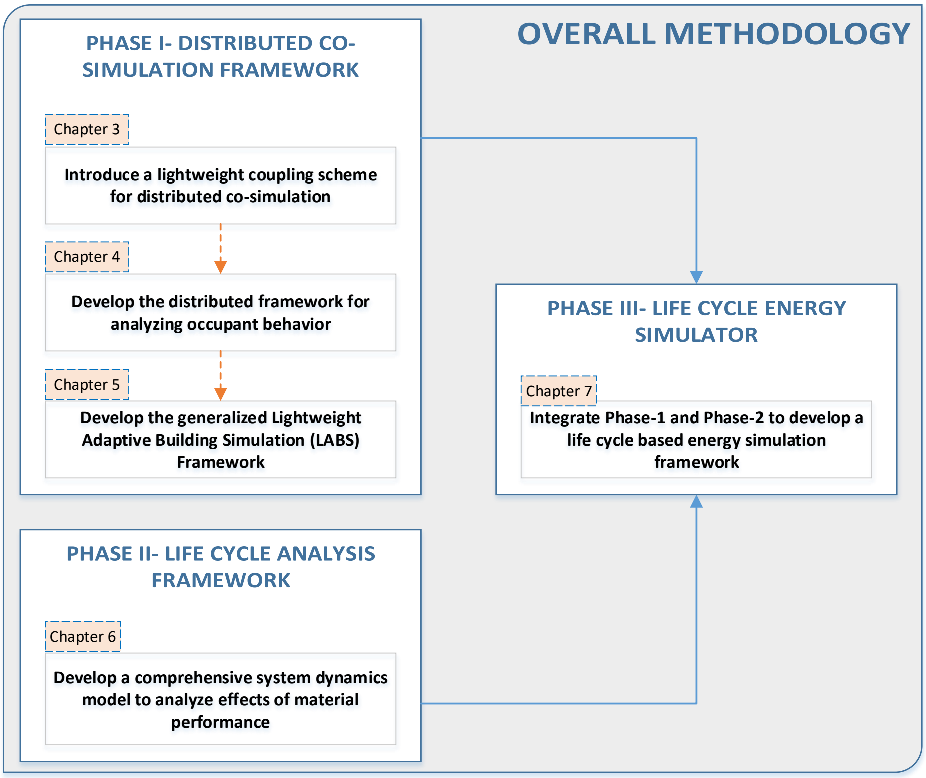

Figure 2-6 Overall Methodology for this dissertation

2.8 Summary

The current energy analysis domain is going in two different tracks, one in performing cumulative based life cycle energy analysis, and the other in terms of analyzing the energy diversity of occupant's energy use behavior. Even though the latter has suggested that, by analyzing the dynamism in a building's operation energy savings can be achieved, there is no focus on analyzing how these savings can be integrated to a life cycle based energy monitoring framework. The primary reason for this state of affairs is that most of the tools/frameworks presently available are developed for addressing a specific objective/problem in the building life cycle energy domain (Menassa et al. 2014, Wetter 2011). Ideally, to offer insights about the maximum energy savings possible from a building's total life cycle, any simulation framework must be able to exploit the individual benefits of all process models collectively (Pang et al. 2012).

Therefore, the current approaches are highly disconnected and there is a pressing need for an inter-dependent simulation system that mimic and analyze the effects of various events in a building's life cycle. Such a system can help the various stakeholders to understand building's energy consumption mechanism better, and devise strategies targeting energy savings. In addition to the focus on achieving energy savings, occupant's thermal and work comfort in the building environment is also of extreme importance as people spend around 92% of their time in indoor building environments (Klepeis et al. 2001). Therefore, understanding and modeling the effects of several factors influencing the energy consumption and occupant's comfort in buildings is a pre-requisite in devising energy efficiency strategies. Chapter 3 to Chapter 7 detail each component that is mentioned in Figure 2-6. Chapter-8 summarizes the verification and validation approaches adopted for the models in this dissertation and Chapter 9 discusses the major findings from this research work and provide the final remarks.

CHAPTER 3

Lightweight Communication and Marshalling (LCM) Framework for Incorporating Occupant Behavior in Energy Simulation

3.1 Summary

This study discusses the limitations of current co-simulation frameworks, and introduces a new coupled simulation concept to analyze the energy effects of occupant's dynamic energy use behavior. This study can also be found in Thomas et al. 2016a.

3.2 Occupant behavior models

Through this study, the authors are proposing to use a new message passing system, Lightweight Communications and Marshalling (LCM) to achieve the overall objective of distributed simulation. LCM originated recently (Huang et al. 2010) in the field of robotics and is widely adopted by various organizations and universities nowadays. LCM's major focus is on simplifying the development and debugging of message passing systems and has been widely used in land, underwater and aerial robotics so far (LCM 2015, Huang et al. 2010). However, LCM has never been used in studying the real-time effect of occupant behavior on energy consumption, and this study will utilize its simple message-passing feature thereby achieving the broader objective of coupling multiple software programs.

LCM uses User Datagram Protocol (UDP) multicasting method (employing a publish-subscribe mechanism) for sending and receiving messages across remotely located workstations (running specific simulation programs; for e.g., ABM, Energy Simulation). Each LCM message (for e.g., a text file with the energy simulation results) is transmitted to a

UDP multicast group wherein the interested subscriber (for e.g., an ABM running occupant behavior simulation) listens to the specific message. The main advantage of LCM is avoiding the use of a middleware or hub thereby allowing the peers to communicate directly. Especially in the field of occupant energy use behavior modeling, a simpler framework as proposed through this study will be easy to use for various building stakeholders in determining the energy impact of various occupancy based energy interventions. Subsequent sections in this paper explain the major components of this proposed coupled simulation framework.

3.3 Major variables affecting energy consumption

To obtain the effects of dynamic occupant behavior patterns on the energy simulation, the major pre-requisite is to understand the major variables influencing the energy consumption. This is one major step in devising any coupling framework. Previous studies have identified some of those major factors. For the residential building sector, Santin (2011) identified five factors as the major behavioral traits that affect the energy consumption. Those are the use of appliances and spaces, occupant's energy intensive actions, occupant's ventilation related actions, media related (operating TV, computer etc.) and thermal comfort related actions. Similarly, another study has found out that turning off appliances when not in use result in an energy savings of overall 38% (Kavulya et al. 2012) in an office environment.

Likewise, another study analyzed the use of various comfort control measures such as opening and closing windows, operating window blinds, heaters and fans by the occupants of naturally ventilated buildings and proposed that these behavioral traits depends mainly on the outside temperature Nicol (2001). The variability of windows opening behavior has also been noted as a significant factor that affect the energy consumption by various other studies (Schweiker et al 2012, Johnson et al 2005). In a similar fashion, Duan et al. (2014) investigated the effect of real time thermostat control on the energy consumption by means of a BCVTB coupling framework. Langevin et al. (2014) also used BCVTB to trigger specific thermal comfort and occupant related behavior outcomes based on zone level thermal conditions, wherein an aggregated behavior outcome drives the next energy simulation time step. The behavior patterns simulated includes clothing adjustments (minor and major), fan on, heater on, window on and thermostat up and down adjustments.

While the focus of the above-mentioned studies was on finding out the specific variables, another set of studies assessed the effect of various discrete or continuous energy interventions on the energy use intensity of the building occupants. It is found out that the energy use intensity of occupants in a building is highly diverse and this can significantly affect the overall energy consumption (Azar and Menassa 2015, Yu et al. 2011, Hoes et al. 2009). Based on the energy use intensity, Azar and Menassa (2012) categorized the occupants mainly into three categories; high consumers, medium consumers and low users, and studied the effects of various energy intervention programs. It is proposed through this study that the interventions (discrete or continuous) can have significant effect on the energy use intensity of occupants, and hence affect the total energy consumption in a building. Discrete energy interventions occur at specific time periods and the examples of discrete interventions include green social marketing campaigns (Mohr 2000) or energy training and educations (Verplanken et al 2006). Continuous interactions include peer pressure and the social interactions between occupants who share an everyday living/working environment. These interventions and practices are proved to have significant effect on the energy use intensities of the occupants.

Azar and Menassa (2015) also suggested that the presence of extreme energy consumers can significantly affect the effectiveness of discrete/continuous interventions and the overall energy consumption in the building. However, the approach considering the energy use intensity has some current limitations. The energy use intensity of an occupant is decided by his/her behavioral traits, and hence the effect of energy interventions needs to be correlated to the behavioral traits of people. The framework adopted in this research analyzes the effects of various energy interventions on building occupant's energy use related behavior by coupling an occupant behavior model with a building energy simulation tool.

3.4 Proposed framework

The overall framework adopted for this study is given in Figure 3-1 below. This layout depicts how an occupant behavior model is coupled with an energy simulation model. The occupant behavior model adopted for this study is an extension to the ABM study carried out by Azar and Menassa (2015, 2014, 2012). This model has the capability to simulate the energy use behavior of occupants in a building subjected to various energy-oriented interventions. The simulation starts by initializing various input parameters (for e.g., number of rooms in the building, number of occupants in each room, frequency of interventions etc.). Each agent in the model (building occupant) has specific energy use characteristics such as energy intensity and variability, and interacts and influence other agent's energy use characteristics.

Based on this energy use behavior, the agents also could reduce/increase their own energy use levels, when subjected to various occupancy interventions. At each time step, the model checks whether an intervention is scheduled, and if yes, the intervention influences the energy use behavior of occupants based on the level and nature of the intervention. The intervention methods studied are discrete interventions such as the energy training and education, and continuous interventions such as peer pressure, energy use feedback and varied connectivity between different occupants. Additional details about the model can be found in Azar and Menassa (2015, 2014, and 2012).

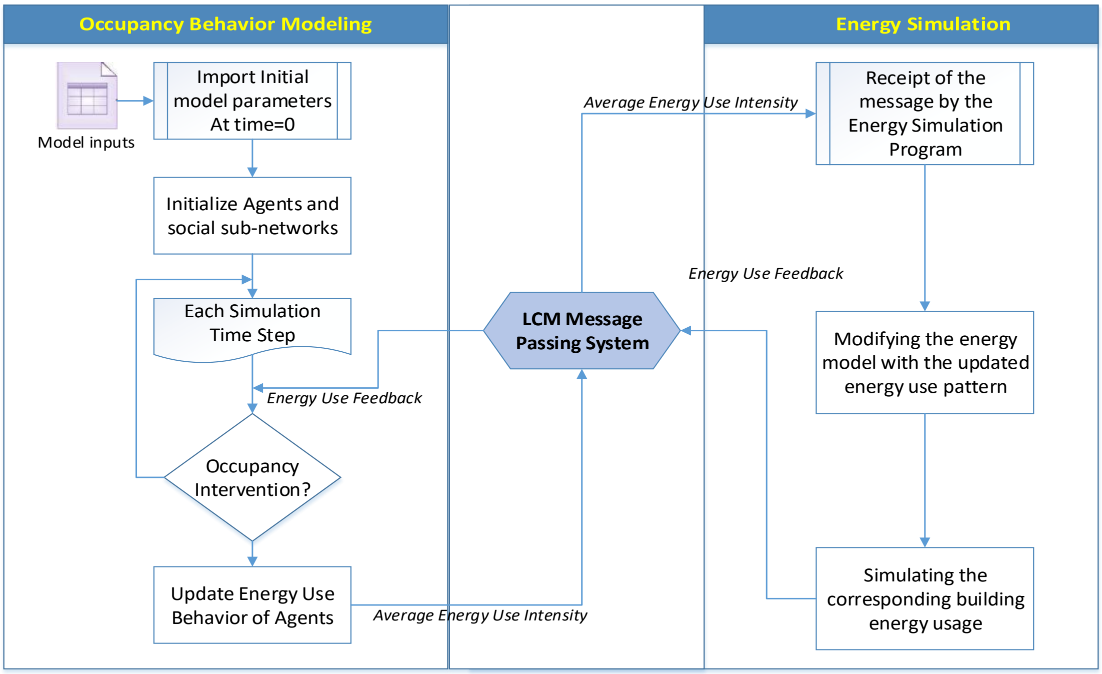

Figure 3-1 Overall research framework

The ABM simulates the energy use intensity of occupants stochastically when subjected to discrete and continuous occupancy interventions. The energy use intensity patterns thus generated are then used to estimate an average energy use intensity that represents the average energy use behavior of all occupants in the building. This value is measured monthly and fed into the energy simulation model via the LCM system. Typically, in commercial as well as residential buildings the energy bill is generated monthly based on the consumption and that is why a monthly time step is adopted in this study to closely align with the real scenario.

Once the energy simulation model receives the predicted average energy use intensity from the ABM, it is compared with the historical energy use data (average energy use intensity one step before i.e., for the previous month) to determine how much relative change has happened in the energy use behavior of the occupants. Based on the percent change (upward or downward), the overall energy use related schedules of the building occupants is modified. Energy simulation models usually use hourly schedules for representing the building lighting usage, the equipment usage, the water heating requirements and the building elevator usage. Based on the percentage change in the occupant energy use behavior, the energy use schedules in the energy simulation model is updated followed by performing the energy simulation for that month. The total energy consumption obtained with this updated energy use behavior is compared with the predicted energy consumption to find out the increase or decrease in the energy consumption. The LCM framework will convey this energy use information back to the ABM model, which will act as an energy use feedback mechanism. This framework combines the effect of all occupant energy interventions and can be utilized by the decision makers in understanding the direct impacts of an energy-based intervention. Given the fact that many organizations are still struggling to design the best energy management practices (IEA 2013) this tool can help the various building stakeholders in determining the best energy reduction initiatives suiting their company objectives.

3.5 Discussion

The contributions of this research towards understanding the overall building energy consumption process are significant. As mentioned in the background section, currently, the energy simulation and occupant behavior modeling is highly separated, and therefore not precisely represent the real scenario. A distributed simulation framework as proposed in this research is a useful tool for making the building energy simulation processes more realistic. Another important contribution made in this research is about adopting a simplified message passing system, LCM. If the coupling platform itself is hard to conceive for the building facility managers, then the usability of the model will become considerably limited and therefore, a simple mechanism as proposed through this study will be a handy one for the various stakeholders to devise energy based intervention strategies.

3.6 Conclusions-Phase 1a

This paper presented a conceptual framework that provides a mechanism to understand the effect of occupant's dynamic energy use behavior on building's energy consumption.

This conceptual framework help the facility managers to visualize the fluctuations in total building energy use thereby allowing them to study the impact of various real time energy based decisions. This framework will also help researchers, policy makers and building managers in designing and implementing the right intervention program that can result in maximum energy savings. In the next chapter, this proposed framework is used to perform a case study and demonstrate how occupant’s energy use behavior influences the energy consumption patterns in the buildings.

CHAPTER 4

Lightweight Coupled System Using the LCM Framework

4.1 Summary

This study developed a user-friendly framework that coupled an adaptive occupant behavior model (OBM) with an energy simulation model (ESM), using the LCM framework proposed through the earlier chapter to analyze the effects of energy based interventions on occupants' adaptive thermal comfort behavior. This study can also be found in Thomas et al. 2016c.

4.2 Coupled simulation framework- Methodology

Figure 4-1 below depicts the overall theme of this proposed framework. Occupants' adaptive behavioral traits (e.g., adjusting thermostat to increase/decrease the room temperature, opening or closing windows to control the air flow in and out of the building) that influence their thermal comfort level are coupled with an energy simulation tool. This coupling allows us to understand the effects of these factors on energy consumption. A coupled system like this could be of use especially to the building facility managers to test the effectiveness of various control and intervention strategies before implementing those in a real building.

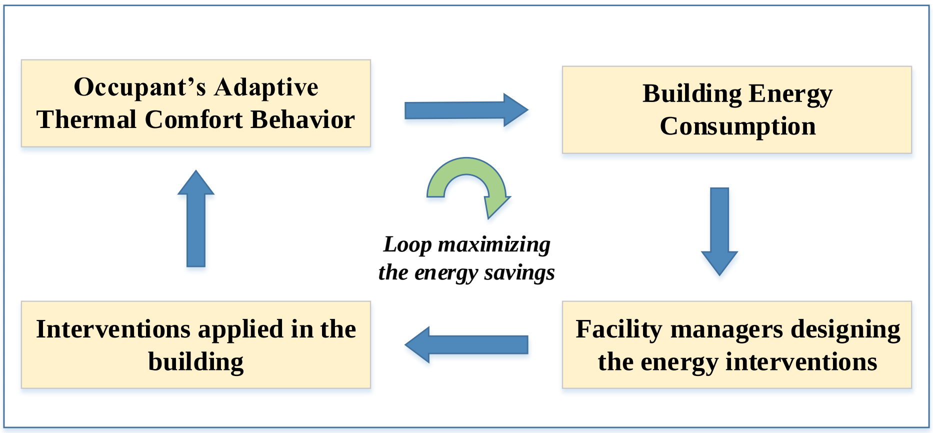

Figure 4-1 Overall theme of coupled simulation framework

Figure 4-2 below gives a conceptual outlay of the framework that explains how an OBM and the ESM is interacting with each other. The OBM in this study is developed using an agent-based modeling (ABM) concept. This ABM is a direct case study application of the model developed by Azar and Menassa (2015, 2013) that originally simulated the energy use intensity of the building occupants based on the relative agreement principles from the social science domain. In the original study by Azar and Menassa, each occupant had attributes such as energy intensity and variability, which was influenced by peer pressure and energy interventions. In our study, these attributes are replaced by occupants' thermal comfort levels (equivalent to the temperature an occupant wants to be set as the thermostat set point) and variability (the range through which the occupant can increase or decrease this preference). For this study, the thermal comfort levels of occupants are randomly generated based on a uniform distribution and this comfort level will be different for winter and summer period. These preferred ranges are adopted based on suggestions from the ASHRAE standard.

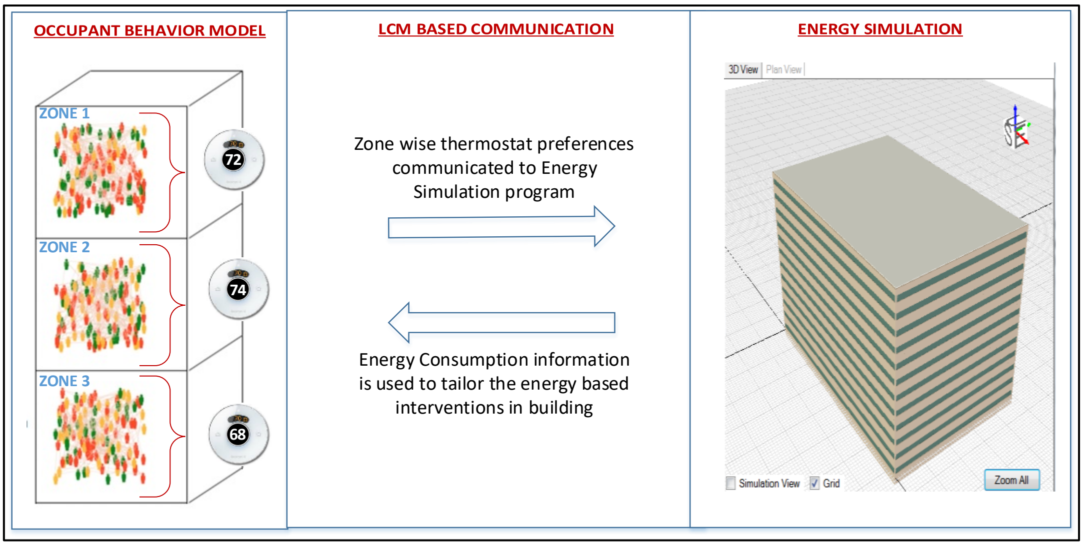

Figure 4-2 LCM Based communication between OBM and ESM

In the OBM, every occupant is connected to a fixed number of other occupants in each zone, which is a factor that can be initialized during the start of the simulation. These connected occupants can be assumed as people occupying the same room. Each occupant can influence the connected occupant's thermal preference thus reaching to a mutually agreed thermostat set point. This action can be considered analogous to the peer pressure concept originally proposed by Azar and Menassa in explaining the dynamic energy use of occupants, i.e., a high-energy user can influence a low energy user and vice versa. Similarly, in this study, the peer pressure will result in occupants interacting and influencing other's thermal comfort level based on the overlap in the preferences between the connected occupants. In the OBM, occupants are represented using three colors, which are red, orange and green. During the winter time, an occupant represented by red color means he/she has a higher temperature preference in the preferred range, and orange and green color denotes progressively lesser temperature preferences. But, during the summer time a red color occupant means the occupant with a lower temperature preference and similarly, orange and green color denotes higher preferences. An overlap means how distant is one's thermal comfort level with the other one's level. If this overlap is large, then that can result in one occupant influencing the other occupant to change his/her preference, and if it is small, the influence does not occur. In a real building scenario, this can be equivalent to a person who is comfortable at a lower thermostat setting during the winter season influencing other occupants to increase their clothing levels, and finally resulting in mutually setting a lower set point for the thermostat.

Eq. 1 and Eq. 2 below shows the calculations involved in preferred thermal comfort level and the variability of the occupants. Readers are encouraged to read Azar and Menassa (2014) for drawing more details about the logic of this ABM.

$$t_j = t_j + \sigma \times \left(\left(\frac{h_{ij}}{v_i} - 1 \right) \times \left(t_i - t_j \right) \right) \quad (1)$$

$$v_j = v_j + \sigma \times \left(\left(\frac{h_{ij}}{v_i} - 1 \right) \times \left(v_i - v_j \right) \right) \quad (2)$$

Where,

t_j *is the desirable thermal comfort level of an occupant j*

t_i *is the desirable thermal comfort level of the connected occupant*

h_{ij} *is the overlap of thermal comfort level between the two connected occupants*

σ *is the peerincrement factor which denotes the effectiveness of the interaction*

v_j *is the variability of the thermal comfort level of an occupant j*

v_i *is the variation of the thermal comfort level of the connected occupant i*

As mentioned before, the comfort level of occupants differs for different zones in the building, and this reflects as varied thermostat set points for each zone. To represent this difference, a mean value is calculated for each zone and is considered as the representative thermostat set points required for that zone. This mean value for each zone is communicated to the energy simulation program at each time step via LCM and this becomes a direct input to the energy model from the OBM. The variable, which is edited in the energy model, is the daytime thermostat set point for the weekday for each zone (i.e., from 8.00 am to 5.00 pm).

Receipt of this message will trigger energy simulation program to start a simulation for a one-month period. For this study, a one-month period is considered as the time step. Once the energy simulation model performs the energy simulation and simulates the energy use information, this information is used to decide how many interventions needs to be performed in the building during the next month to influence the thermal comfort level of the occupants. Figure 4-3 below shows the time synchronization diagram for this study and the logic adopted for deciding the number of interventions.

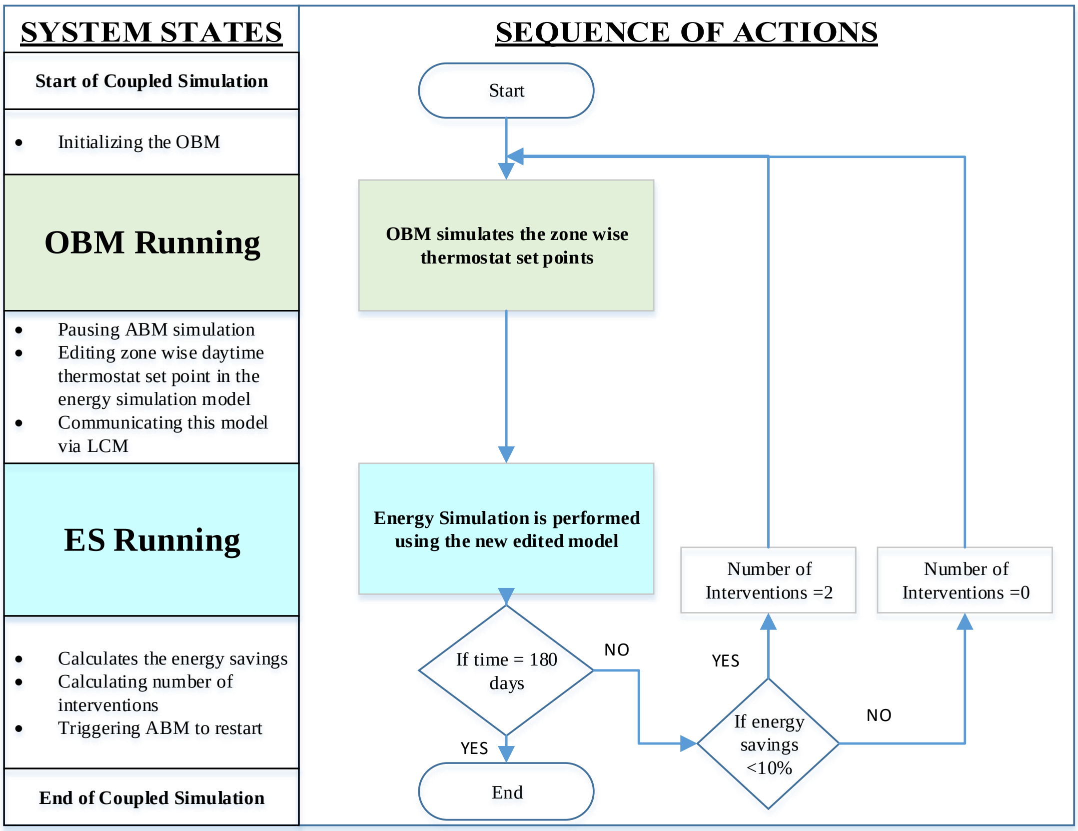

Figure 4-3 System States and sequence of action

Prior to the start of the coupled simulation, an energy simulation is performed using the default energy simulation model to obtain the predicted energy consumption values for the specified time (for e.g., six months, one year). Now in the OBM, for the first month, only the peer pressure is present, which means there are no interventions planned. At each time step, LCM will send the edited energy model to the workstation where energy simulation is programmed to run and will trigger starting the energy simulation automatically, while pausing the OBM. Once the energy simulation is over, this trigger sending the energy use information back to the first workstation, which has the OBM running. This bi-directional information exchange occurs automatically for any specified period (i.e., six months, one year as specified by the user).

Upon receipt of the energy use information, the OBM calculates the difference in the predicted (base case) versus the actual energy consumption, and determines the energy interventions to be planned for the next month. This is what mostly happens in any building. If the energy use is not occurring as per the expectations of the facility managers, then appropriate measures need to be carried out in the building for the next period. These interventions directly influence the occupants to adapt a different thermal comfort level. Once the number of energy interventions is calculated, this will trigger the OBM to restart and run the simulation for the next month based on the latest information. The interventions are designed in such a way that the occupants with adverse temperature preferences (occupants who would like to have a higher thermostat set point in the winter time and a lower thermostat set point in the summer) would be targeted more. Adopting a strategy like this could result in influencing them to adapt better behavioral preferences such as increase the clothing levels when cold, taking off some extra level of clothes in hot weather, and opening the windows to allow natural ventilation in summer (Fabbri 2015).

Eq. 3 below gives the way occupant's thermostat set point preference is modified by an intervention. Intervention efficiency in the equation refers to the type of intervention that is planned in the building. Common interventions methods adopted by the facility managers are education programs (posters, mobile applications) and monetary rewards, and the intervention efficiency varies across different intervention programs. The factor γ in the equation is designed to specifically focus on diverse types of occupants, and this varies from 0 to 1. For adverse occupants, the value will be typically set at '1' which means targeting to influence their set point preference with the maximum intensity. This cycle will continue for any defined period by the user such as six months or one year, and the energy savings for this entire period will be recorded for further drawing further inference.

$$t_i = t_i \times (1 - \gamma * uniform(0, intervention\ effciency) \quad (3)$$

Where, t_i *is the comfort temperature of occupant i*

γ *is the factor that control the level of an intervention.*

4.3 Case Study

As mentioned earlier, the main objective of this paper is to propose the usability of LCM as a coupling aid. Hence the focus of validation of the framework is to model the energy effects of the zone wise thermal comfort level preferences of occupants in an office building using the OBM, and demonstrate the exchange of variables between the OBM and the ESM. For conducting detailed validation techniques such as historical validation or multistage validation, the major pre-requisite is the availability of adequate data points (in this case, the actual thermal comfort levels of the building occupants over a specified period) (Sargent 2000). The ongoing study is collecting those personnel comfort level data of occupants and hence the validation adopted in this paper is limited to technical validation, i.e., focusing on the technical and computing and data exchange mechanism of the framework.

Energy Plus is selected as the energy simulation software (EnergyPlus 2012). A medium sized office-building model provided by the Department of Energy is adopted as the ESM (DOE 2015). As was previously mentioned in the methodology section, the OBM is a direct case study application of the earlier published study (Azar and Menassa. 2015, 2013). Brief details about the ESM and the general simulation details are summarized in Table 4-1 below. A total simulation for six months consisting of three winter months (January, February and March) and three summer months (April, May, June) is considered as the run period of the coupled framework. The zone wise thermostat set points are dynamically simulated as per the OBM logic outlined in the above methodology section. The allowable temperature ranges for the thermostats are decided based on the ASHRAE recommended temperature ranges as given in Table 4-1 below.

Table 4-1 Case study building details

Item	**Description**
Location of the building	Chicago
Type	Office
Shape	Rectangle
Building length	73.11m
Building width	48.74 m
No of stories	12 stories plus basement
Gross area	46, 320 sq. m
Number of zones	18
Occupancy in	16 zones
Number of total Occupants	2,397
Winter temperature range in degree Celsius	15.5-21
Summer Temperature range in degree Celsius	21-29

Before starting the co-simulation, an EnergyPlus simulation is conducted for six months with the default energy model to obtain the energy consumption details for the base case, i.e., with fixed zone wise thermostat set points. After obtaining this default energy consumption for every month, the real co-simulation is started by invoking the OBM. At each time step, i.e., one month in this case study, the OBM creates a new ESM with revised zone thermostat schedules. Creation of this new model will trigger EnergyPlus to start an energy simulation, in a different workstation with the modified ESM. Once the EnergyPlus simulates the energy consumption for that time step, this energy consumption information will be conveyed back to the OBM. Upon receipt of this energy consumption information, the number of interventions for the next month is estimated and the OBM will proceed with the simulation for the next time step. This process is repeated for the specified time (i.e., six months here) and that completes one typical co-simulation. The actual energy consumption details can then be compared with the base case to calculate the overall savings possible. These inter communications are made possible with the help of LCM.

4.4 Results and discussions

The results from this coupled simulation is shown in Table 4-2. In the six-month period, 10 interventions are implemented in the building (Two interventions applied for every month, from February through June). This has resulted in drifting occupants' comfort temperature levels downwards during the winter months and upwards during the summer months, which eventually resulted in an overall energy savings of around 10%.

Table 4-2 Energy consumption details

Month	Energy Use in GJ (Base Case)	Energy Use in GJ (with energy interventions)
January	3938.125	3551.79
February	3153.28	2868.05
March	2575.519	2249.16
April	2,184.22	2173.02
May	2,093.09	1829.13
June	2,232.08	2091.7
Total	**16176.316**	**14762.85**

The main contribution from this study is the coupled framework using LCM. Once actuated, the framework runs and exchanges information between the contributing programs for the specified period, automatically. In addition, this does not involve any middleware to control this coupled simulation. Such a system could be of use to create efficient coupled frameworks in various domains of civil infrastructure systems. Another major inference from this study is about the energy savings possible by controlling and influencing the temperature preferences of the building occupants.

4.5 Conclusions-Phase 1b

Through this study, a framework that couples an OBM and an ESM is created and the energy effects of adaptive thermal comfort behavior of the occupants were tabulated. This general framework can be extended to analyze the effects of many other behavioral traits of building occupants. The building managers can use this framework to show the building occupants about the possible energy saving opportunities by adopting good thermal comfort related behaviors. While this study developed the preliminary framework with a sequential coupling scheme, through the next chapter a runtime coupling mechanism is developed that allows a generalized distributed co-simulation framework for coupling different modules in the building energy analysis domain.

CHAPTER 5

Generalized Lightweight Adaptive Building Simulation (LABS) Framework for Distributed Co-Simulation

5.1 Summary

The frameworks developed through Chapter-3 and Chapter-4 have highlighted the importance of coupled simulation to analyze the energy effects of several dynamic factors in buildings. These frameworks have also put forward the need of connecting distributed simulation models running in remotely located work stations. Therefore, through this chapter, an innovative distributed co-simulation framework, LABS (Lightweight Adaptive Building Simulation) is developed using the capabilities of Lightweight Communications and Marshalling (LCM). The approach proposed through this study introduced more flexibility to analyze the energy effects of occupant's adaptive energy use behavior. This study can also be found in Thomas et al. 2017a.

5.2 LABS Framework

For creating a coupled system across different workstations using LCM, the first and foremost requirement is to build/install LCM in all the workstations. LCM is an open source software and can be built in Windows, Macintosh and Ubuntu platforms (LCM 2015) with much ease. LCM eliminates the need for a middleware and allows each of the contributing programs to interact directly. Figure 5-1 below demonstrates a typical instance of a push-based *"publish-subscribe"* mechanism generally employed by the LCM framework. LCM utilizes a User Datagram Protocol (UDP) multicasting method for sending and receiving messages across the workstations. There is a publisher (in a work station) who sends data packets to designated channels. Interested subscribers can listen to that channel and accept the data packets. At the same time, a publisher can also act as subscriber to the messages coming from other publishers. Figure 5-1 demonstrates only one such instance where a publisher sends a message to many subscribers.

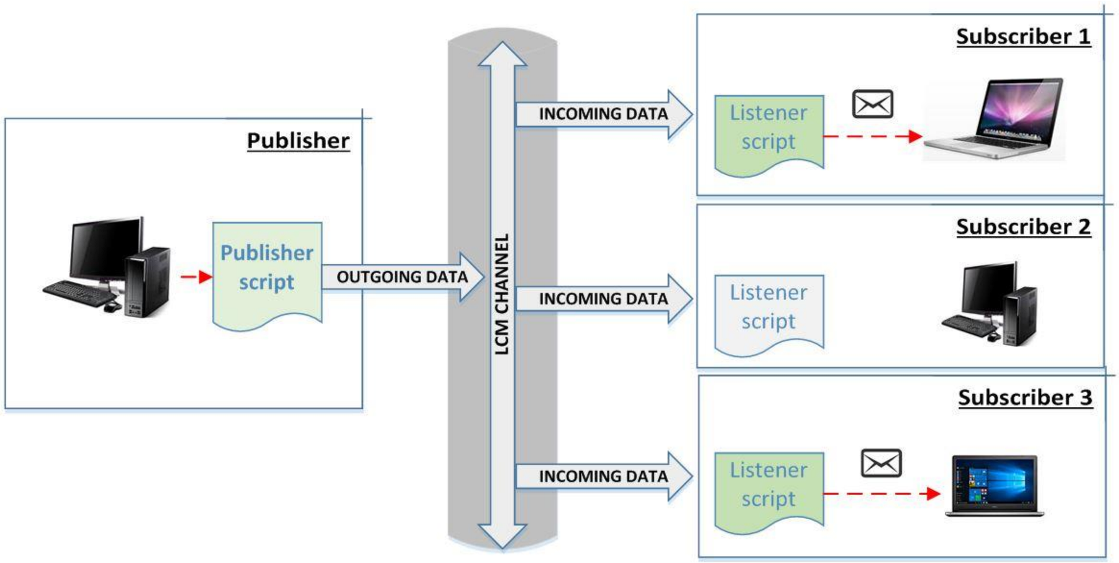

Figure 5-1 General LCM Mechanism

A typical example of such a message transfer can be the energy simulation program publishing the zone wise ambient temperature information at each time step. In a coupled energy simulation context, a typical subscriber to this information can be an occupant behavior model that wants the zone temperature at a time step for deciding occupants' response to the ambient condition in the room. The message received by the subscriber will trigger setting up an action in the subscriber's workstation. In Figure 5-1, subscriber-1 and subscriber-3 are interested to receive this information whereas subscriber-2 is not interested in this data packet. But, subscriber-2 might be receiving information from other publishers. The subscribers decode the received data packet, process the information, and might send latest information back to the LCM channel (in this case, acting as publishers). A publisher script and a listener script are basically computer programs developed in languages such as python, java, C++, Matlab using the LCM bindings to facilitate the sending and receipt of this message by individual work stations. Currently, the work stations need to be connected to the same network. The network does not require an internet connection, but the work stations need to be within the same local network. LCM also has the capability to pass messages across networks, and incorporating those features into this framework is being explored as part of our ongoing work.

In the LABS framework, an adaptive co-simulation strategy wherein all the contributing programs in the network run in parallel, and exchange information during the runtime is proposed. LCM manages the sending of the data across the workstations, whenever required. In such a scheme, one important aspect that needs to be addressed is the time synchronization between the contributing programs. For achieving this, the framework is considered as a collection of primary and secondary programs. A primary program is the one that takes information from all the secondary programs during each of its time steps. In a building energy simulation context, the primary program would be the energy simulation program and secondary programs can be an occupant behavior model simulating occupant's energy use behavior (e.g., opening or closing windows, adjusting thermostats, operating lighting and equipment fixtures) or HVAC based controllers (e.g., shading controllers, air flow controllers).

Determining a common time step is very important in this context as it defines the frequency at which the messages would be exchanged between different programs. This time step can be the user's sole choice (typically, fifteen minutes to one hour) and every program in the system (primary and the secondary programs) need to follow the same time step for synchronizing the time step of the co-simulation. Once the time step is defined, the next requirement is to define the variables to be exchanged between the publishers and the subscribers at each time step. Each workstation will have LCM scripts in action, to publish as well as subscribe to the messages. For achieving the time synchronization, a pause-wait-restart logic is proposed and is shown in Figure 5-2 below.

Figure 5-2 explains the logic through one primary and one secondary program. The primary program pauses at each time step and exchanges information with the secondary program, and then waits for the secondary program to reach to the primary program's time step. Adopting an approach like this is necessary because the runtime mechanism of every simulation program differs and adopting this technique ensures that no message drop occurs during the co-simulation. If there are more than one secondary programs, then the primary program waits till the message is received from all the programs. Once the message is received, it processes the received information and exchanges latest information back to the primary program. This will trigger the primary and the secondary programs to restart and continue from the previously reached time step. From an execution point of view at the primary program side, sending the message, waiting for the message and restarting the simulation (i.e., each time step advancement) will typically require under one second of wall clock time.

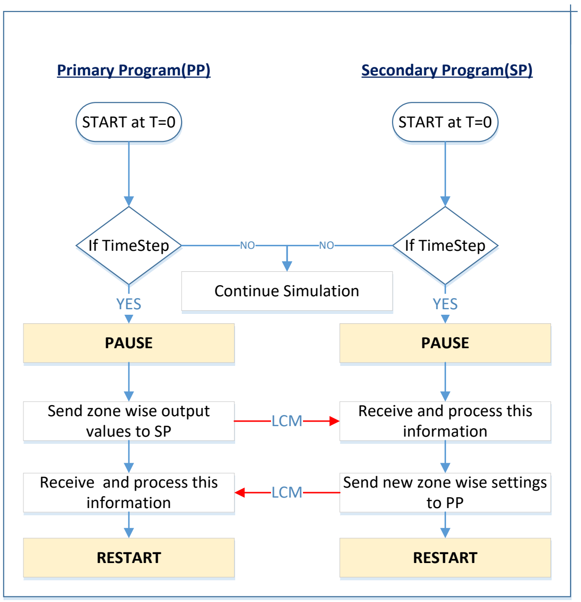

Figure 5-2 Pause-Wait-Restart Strategy

A typical example for this can be adapted from the building performance simulation context itself. An energy simulation (ES) program can be the primary program wherein an occupant behavior model (OBM) can be the secondary program, and the data exchange happens at every zone time step of the ES. The ES running in workstation-1 can be sending the zone wise comfort level of building occupants, and in response to that information, the OBM running in workstation-2 can send back the new thermostat set points to be set in ES for the next time step.

One critical point to note here is that, along with the execution of the primary program, there can be actions happening in the secondary program as well. For instance, at a time step different than the primary program, there might be an energy intervention (typically, a discrete event in the OBM) targeting the energy use behavior of the occupants. In a BCVTB/FMU scheme representing the effects of an action happening in slave programs, in a time step apart from the master programs is not possible. In LABS, by adopting a pause-wait-restart mechanism, the adaptation happening in all the secondary programs also can be effectively represented, because all the programs run continuously.

In the case study which is explained below, there are intervention strategies which are planned as discrete events occurring in the OBM. These events occur at time step other than the primary energy simulation model time step, and by adopting a technique like this, the changes occurring in the secondary program can be communicated effectively. Similarly, the peer pressure effects that occur continuously between the occupants in a building can also be represented by this approach. Therefore, in order to represent such a scheme the programs need to run in parallel with options of incorporating the effects of events in all the secondary programs as well. This idea is one important contribution from this study as it can help to effectively portray the continuous adaptation in the building system.

Figure 5-3 below provides a detailed explanation on the actions occurring at a typical time step, across the two programs. Both the workstations will have an LCM-publisher and an LCM-listener in action. As a first step, the primary program writes the output data to a text file. It also modifies two placeholder text files with the text "WAITFORSP" and "SENDTOSP" subsequently. The primary program will restart again only when the text in placeholder-1 is changed as "RESTART". So, in effect, the text edit in placeholder-1 will pause the execution of the primary program temporarily and the text edit in placeholder-2 will trigger the LCM-publisher to send the primary program output data to the workstation-2. The LCM-listener at the workstation-2 will receive this information instantly. When the secondary program reaches to the same time step as the primary program, it processes this information and writes the data to the primary program in a text file. In addition, a similar placeholder at this workstation will be edited as "SENDTOPP" which will trigger the LCM-publisher to send the data back to the workstation-1. Once the LCM-listener receives this message at the workstation-1, it reinstates the text in placeholder-1 as "RESTART" and this will enable the primary program to restart from the paused state.

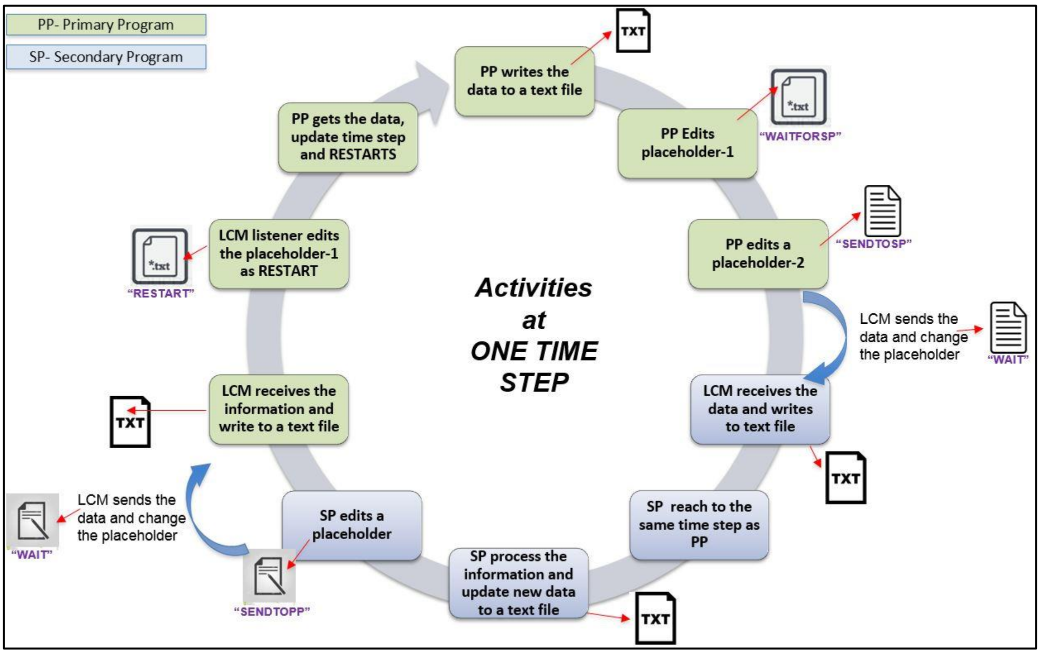

Figure 5-3 LCM message sending and receiving methodology

The LCM-publisher and the LCM-listener are developed in c-language. The LCM-publisher continuously looks for the text in placeholder text files, and publishes the information whenever there is an edit in the respective placeholder text. The LCM-listener will instantly subscribe the message published by the publisher. These steps will be repeated at every time step of the simulation. For instance, if the total time frame of the simulation run is 24 hours, and if the time step is 1 hour, then the actions described in Figure 5-3 will occur at each time step, i.e., total 24 times.

5.3 Case study

In order to demonstrate the capabilities of the LABS framework, a building energy simulation model is coupled with an occupant behavior simulation model. An inter-connected framework like this is significant as the traditional energy simulation programs (including EnergyPlus) assume a pre-defined pattern of building performance parameters (e.g., fixed heating and cooling schedules, fixed seasonal clothing values). This does not mimic the actual scenario because occupants' energy related behavior in buildings can undergo tremendous variations, and there is a need for a more realistic way of representing this. In addition, inspired by studies that established the energy saving opportunities because of adaptive behavioral patterns of occupants interacting together in a given space (Thomas et al. 2016b, Kashif et al. 2015, Zhao et al. 2014, Langevin et al. 2014, Menassa et al. 2013, Azar and Menassa 2012), effective ways of controlling these behavioral patterns could also provide insight into optimizing the energy consumption in the building while maintaining occupant comfort.

EnergyPlus V 8.5 is used as the energy simulation engine. The case study analysis is performed for a small sized building located at Chicago. This building energy model is one of the example office building models that come along with the installation of EnergyPlus software (DOE 2017). From these example models, the model selected for this case study is "*RefBldgSmallOfficeNew2004_Chicago.idf*". This building is a single storied, five zone office building (one core and four perimeter zones) with a total floor space of 511 m^2 and a window to wall ratio of 21.2%. The building has a default heating and cooling schedule and using the LABS framework, the effects of occupants' adaptive energy use behavior for a day in the winter season is simulated. Table 5-1 below summarizes some of the major characteristics of this building and Figure 5-4 below shows an image of the building model developed using Simergy v2.5, a graphical user interface for EnergyPlus (Simergy 2017).

Table 5-1 Case study building details

Item	**Description**
Location	Chicago
Type	Office
Latitude	41.77 degree
Longitude	-87.75 degree
Shape	Rectangle
Building length	27.69 m
Building width	18.46 m
No of stories	1
Gross area	511 m^2
Number of zones with occupancy	5
Number of Occupants in each zone	10
Day of Simulation	A typical office day in the Winter (January 5th 2016)
Occupancy Schedule	Till 8.00 am- No occupancy considered 8.00 am to 5.00 pm- 100% Occupancy considered 5.00 pm to 12.00 pm- No occupancy considered
Default Heating Schedule	Till 8.00 am- 15.6^{o}C 8.00 am to 10.00 pm- 21^{o}C 10.00 pm to 12.00 pm- 15.6^{o}C

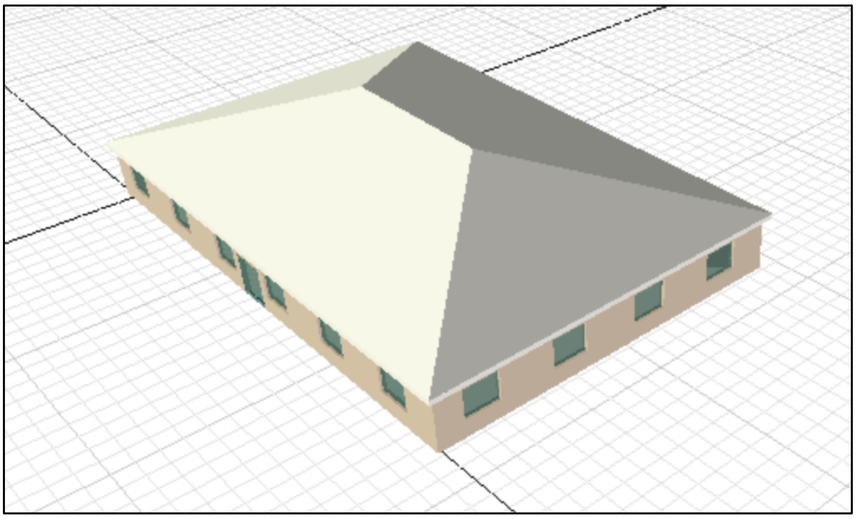

Figure 5-4 Case study building model at Chicago

For this study, EnergyPlus is built from its source code and the simulations are run through the command terminal (NREL 2016). This approach is adopted to facilitate accessing the run time variables and schedules from EnergyPlus. In BCVTB and FMU, this functionality is provided by means of the *ExternalInterface* module in the EnergyPlus. This module accesses the runtime variables (e.g., zone wise air temperature) from the master program (EnergyPlus), exchanges it with the slave program, and based on the outputs from the slave program, the relevant schedule values in the master program are modified (e.g., zone wise thermostat set point). In the source code, the program *SimulationManager.cc* manages the simulation time steps and the function *ExternalInterfaceExchangeVariables()* within this program establish the message exchange mechanism with the slave programs. By investigating this function deeper, we learned that the capabilities of two other functions in the source code can be utilized for accessing the variables and modifying the schedules. Those are *GetInternalVariableValueExternalInterface()* and *ExternalInterfaceSetSchedule()*. The first function is used for accessing the runtime variables and the second function is used for modifying the schedules. Hence, in the *SimulationManager.cc* we first disabled the *ExternalInterfaceExchangeVariables()* function (the function that established the message exchange mechanism for BCVTB and the FMU). Subsequently, during the EnergyPlus runtime, we directly accessed and modified the variables and schedules using the functions, *GetInternalVariableValueExternalInterface()* and *ExternalInterfaceSetSchedule()*.

At each time step of the EnergyPlus simulation run, the variables accessed through the above function, *GetInternalVariableValueExternalInterface()* are written to text files, which are directly accessible by the LCM-publisher to send to the OBM. Similarly, the new schedule values obtained from the OBM as an LCM message are used to modify the EnergyPlus schedule using the function *ExternalInterfaceSetSchedule()*. By adopting this mechanism, the complexities for reading and modifying the variables and the schedules in the EnergyPlus is significantly reduced. This also allows the programs to interact directly using a text file based data exchange mechanism.

The OBM in this study is developed through the multi-method simulation-based tool, Anylogic V 6.8.1, and is a direct case study application of the OBM developed by Azar and Menassa (2015, 2013). This OBM used an agent-based modeling (ABM) concept to replicate the thermal comfort related actions of the occupants in the energy simulation model. Occupants' thermal comfort is of extreme importance as people spend around 92% of their time in indoor building environments (Klepeis et al. 2001), and their living comfort can also affect their work productivity. Usually, in a climate-controlled building, the HVAC system ensures appropriate thermal comfort levels to the occupants by means of controlling the cool and hot air flow through the ducts. The most common approach for measuring the thermal comfort is the Predicted mean vote (PMV) (Ku et al. 2015, Fabbri 2015, Fanger 1970). The original PMV measure proposed by Fanger (1970) represents the thermal sensation levels of the occupant in a seven-point scale and it depends upon building's ambient conditions as well as occupant's activity levels and the clothing levels. In an office-building environment, the activity level of the occupants can be assumed as a fixed value as the activities are basically sitting or light walking. However, one major action the occupants usually adopt on a real-time basis is to vary the clothing level (e.g., wearing an additional sweater if feeling cold or remove an extra layer of clothing, if feeling warmer) (Langevin et al. 2014).

Other actions building occupants perform to achieve comfort include adjusting the thermostat level, opening or closing the windows in summer season, or using the option of a personnel heater or fan. This case study will measure how clothing level can be influenced to set optimum thermostat set points thereby exploring the possibility of achieving energy savings, without compromising on the thermal comfort. In this study, the thermostats are assumed adjustable and the occupants are willing to increase or decrease their clothing levels within the acceptable levels. Typically, in an office environment, even though everyone might not be willing to wear an additional layer of clothing all the time, the peer pressure among the occupants and the energy-based interventions might result in a positive behavioral change and this assumption is made only to highlight the energy savings possible if everyone follows this approach in an office setting.

The default energy model has the same heating set point schedule and clothing schedule assumed for all the zones. For a typical weekday, the default heating set point schedule for all the zones assume 15.6^{o}C till 8.00 am, 21^{o}C from 8.00 am to 10pm and from 10pm till 12 pm midnight the thermostat settings are set back to 15.6^{o}C. Meanwhile, in the default clothing schedule, the clothing levels assumed for the winter period is 1.0 Clo. In climate controlled buildings, the heating and air conditioning systems do not maintain a uniform temperature throughout the building, and different zones and different rooms in each zone will have slightly varying thermostat set points. This is mainly because of diverse thermal comfort preferences of people occupying these areas and proximity of some zones with respect to the outside environment (e.g., perimeter zones compared to core zones). Similar is the case with the clothing levels as the occupants will be frequently changing their clothing levels. Hence, for each zone with occupancy, a separate heating schedule and clothing schedule is created in the EnergyPlus model and these schedule details would be received from the OBM at every time step. As was previously mentioned, the OBM for this study is a modified case study application of the ABM developed by Azar and Menassa (2015, 2013) that originally simulated the energy use intensity of the building occupants based on the relative agreement principles (Deffuant et al. 2006, 2002) from the social science domain.

In the original study by Azar and Menassa (2013), each occupant had attributes such as energy intensity and a variability (the range through which the occupant can increase or decrease their energy use preference) and simulated the energy use behavior of occupants in a building subjected to various energy-focused interventions. The simulation starts by initializing various input parameters (e.g., number of rooms in the building, number of occupants in each room, frequency of interventions etc.). Each agent in the model (building occupant) has specific energy use characteristics such as energy intensity and variability and interacts and influences other agent's energy use characteristics. Based on this energy use behavior, the agents also have the opportunity to reduce/increase their own energy use levels when subjected to various occupancy interventions. At each time step, the model checks whether an intervention is scheduled and influence the energy use behavior of occupants based on the level and nature of the intervention. The intervention methods studied are discrete interventions such as energy training and education and continuous interventions such as peer pressure, energy use feedback based on varied connectivity between the different occupants.

For our study, each occupant's energy use attributes are changed to the clothing level and its variability. The ranges through which the clothing levels are varied are explained in the subsequent sections below. The desired thermostat levels by the occupants are not considered as an attribute and is assumed as a derived value which is influenced by their clothing levels and the building ambient parameters. Reusing an old simulation model like this for solving a new problem could be achieved only because of the versatility provided by the LABS framework. Figure 5-5 below shows the data exchange and time synchronization mechanism adopted for this study. A one-hour period is selected as the time step across the ES and the OBM, which is reasonably a good interval for occupants to modify the clothing level and the corresponding thermal preferences. As mentioned in Figure 5-2, the pause-wait-restart mechanism allows synchronizing the data exchange across ES and OBM. Here, ES acts as the primary program that controls the pause and restart scheme.

During time period-1 (i.e., till 8.00 am in the morning), no occupancy is considered and hence upon receipt of the building ambient parameters from the ES, OBM exchanges a message "DEFAULT" which will trigger ES to advance to the next time step with the default schedule values. In the second-time period (i.e., from 8.00 am to 5.00 pm), occupants arrive to the office and at every time instant, building's ambient parameters will be exchanged from ES and occupant's clothing and activity levels in the OBM determines the thermal sensations (PMV levels) of the occupants. At each time step, occupants are given an opportunity to vote their thermal preference based on a seven-point scale. Similar voting approach is adopted in many studies to represent the thermal preference of occupants (Erickson and Cerpa 2012; Daum et al. 2011; Feldmeier and Paradiso 2010). Based on the average vote from each zone in the building, a new thermostat set point for that zone is conveyed to the energy simulation model. Time period-3 is similar to time period-1 in terms of occupancy and the data exchange. The coupled simulation will end when the time in primary program reaches 24 hours (i.e., one day).

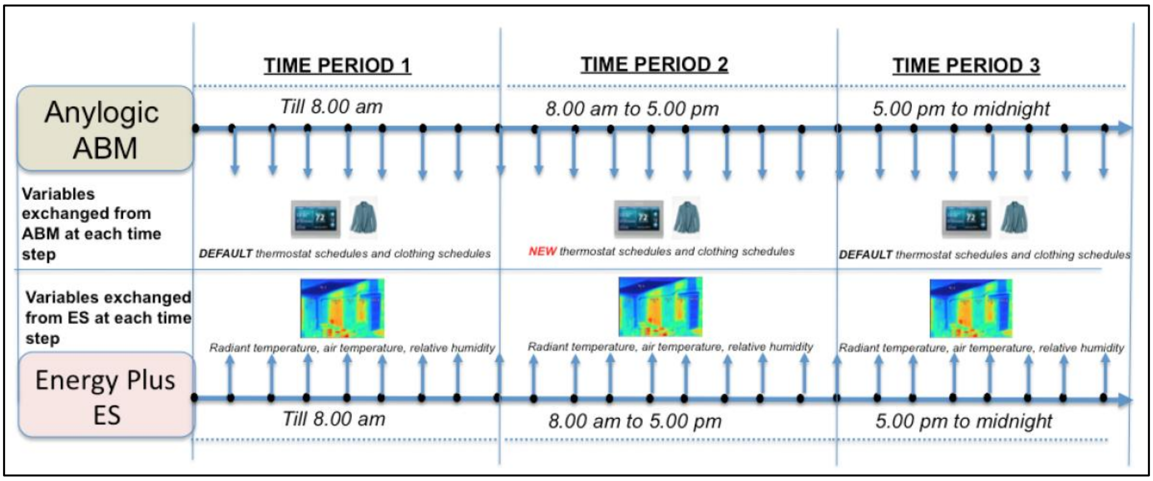

Figure 5-5 Time synchronization diagram

As mentioned earlier, the message exchange in the LABS framework is facilitated using LCM and every workstation in the loop should have LCM-publisher and LCM-listener programs. Table 5-2 and Table 5-3 below explain the actions that occur for sending EnergyPlus data to OBM and OBM data to EnergyPlus. WS1 refers to workstation-1 where the EnergyPlus runs (A Windows computer) and WS2 refers to workstation-2 where the OBM runs (An OS X computer).

Table 5-2 Sending data from EnergyPlus to OBM

In WS1: Publisher.c (A c-program)	In WS2: Listener.c (A c-program)
Continuously checks whether placeholder-2 is getting updated as "SENDTOABM"	This listener receives data from work station-1, i.e., the building ambient parameters.
Once this trigger happens, it sends one single message and changes the text in placeholder-2 back as "WAITFORABM"	This message is the string with values separated by "*"
A message is a single string	Whenever the message is received, this data will be decoded and will be written to the textfile-1
This string comprises of all the data from ES at a time step (the building ambient parameters), separated by "*". For example, 21.0*20.8*9.5* …	OBM reads the information in textfile-1 for processing

Table 5-3 Sending data from OBM to EnergyPlus

In WS1: Publisher.c (A c-program)	In WS2: Listener.c (A c-program)
Continuously checks whether placeholder-1 is getting updated as “SENDTOES”	This listener receives data from work station-, which are the new thermostat schedules and clothing schedules.
Once this trigger happens, it sends one single message and changes the text in placeholder-1 as “WAITFORES”	This message is the string with values separated by “*”
A message is a single string	Whenever this message is received, this data will be decoded by this program and will be written to the textfile-2
This string comprises of the thermostat settings and the clothing schedules for all zones, separated by “*”. For example, 21.0*20.8*19.5* …	After receiving this message, placeholder1 will be updated with “RESTART” which will trigger restarting the ES.

The detailed steps involved in this coupling scheme along with the OBM logic are explained through Figure 5-6 below. As mentioned earlier, a typical office day is divided into four periods, before regular office time (Midnight to 8.00 am), when occupants arrive at the office (At 8.00 am), during the office time (8.00 am to 5.00 pm), after the office time (5.00 pm to 12.00 pm).

5.3.1 Period 1: Before regular office hours

Till 8.00 am, no occupancy is assumed which means the temperature can be set at a minimum value of 15.6 degree Celsius for all the zones. The message sending sequence is programmed in such a way that the building ambient conditions are still sent across to the OBM. Since there is no occupancy in this period, the OBM exchanges a message “DEFAULT”, which will instruct the ES to consider the default thermostat schedule values. This way of programing gives the flexibility to extend this framework if there is an occupancy that needs to be considered in this period, in the future. Therefore, even though the ES also has the default thermostat settings, for allowing a common data exchange scheme, this value is programmed to be received from the OBM.

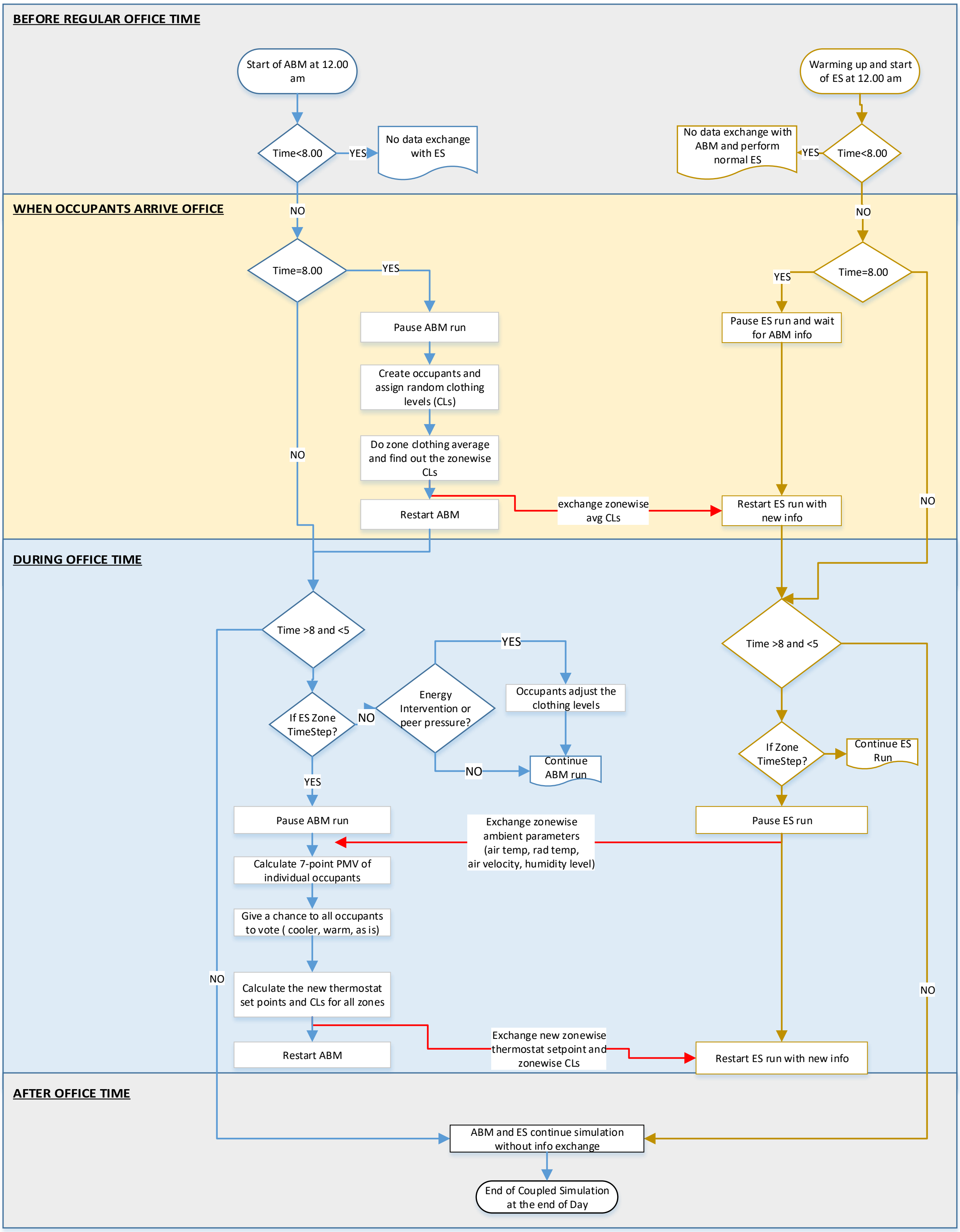

Figure 5-6 Flowchart demonstrating the OBM logic

5.3.2 Period 2: When occupants arrive to the office

At 8.00 am, occupants arrive to the office. The total occupancy in the building is 50 and each zone has 10 occupants. Each occupant will be assigned a clothing level when they arrive, and is stochastically allocated between 0.3 Clo to 1.3 Clo, based on a uniform distribution. Langevin et al. (2015) considered a similar clothing range of 0.3 to 1.3 for a typical office atmosphere. In addition, Zhao et al. 2015 considered a range of clothing values from 0.4 Clo to 1.9 Clo. Hence a clothing range of 0.3 Clo to 1.3 Clo fairly represents the variability in the clothing levels of occupants, given the fact that the default clothing value in the model is 1.0 Clo. Along with this assumption, each occupant is also allocated a clothing variability. This variability refers to the change in the clothing levels each occupant can bring in when subjected to the varying building ambient conditions, and the various energy based interventions in the building. It is determined based on a simple rationale explained through Eq. 1 below. This equation allocates the clothing variability to each occupant based on the upper and lower limits of clothing level range.

$$cv_i = \begin{cases} 1.3 - c_i, & c_i > 1 \\ c_i - 0.3, & c_i \leq 1 \end{cases} \tag{1}$$

Where,

c_i *is the clothing level of an occupant* i
cv_i *is the clothing level variability of occupant* i

In an office environment, the interaction between occupants are typically high and this will have an effect on energy based interventions to travel across very quickly. To better understand how occupants, interact and respond to interventions, researchers have analyzed the social structure/network of the occupants in the building (Azar and Menassa 2015, 2013, Anderson et al. 2013, Chen et al. 2012). Such a methodology can help in analyzing how peer pressure can determine how energy interventions percolate through a collection of people.

Hence, after allocating the variability, a network structure is assumed between the occupants, which essentially introduces the connection between the occupants. In each zone, the network structure is also randomly selected among the small-world or scale-free types (Barabasi et al. 1999, Watts and Strogatz 1998), which are commonly adopted types for learning human's interaction. Once this network structure is allocated, a zone average clothing level is calculated and the default thermostat schedule value is set as 21.0 Degree Celsius for all the zones. Both this information is communicated to ES and at 8.00 am.

5.3.3 Period 3: During the regular office hours

From 8.00 am onwards, the occupants interact and work together at their work place. Every occupant is connected to a number of other occupants in each zone, which is a factor that can be initialized during the start of the OBM simulation. These connected occupants can be assumed as people occupying the same room. There can be occupants with a higher clothing level, medium level and lower level. Higher clothing level occupants can possibly influence the lower clothing level occupants to increase their clothing, which is analogous to the peer pressure concept originally proposed by Azar and Menassa (2013) in explaining the dynamic energy use of occupants (i.e., a high-energy user can influence a low energy user to turn his behavior and vice versa). Similar concepts of coordination can also be seen from the literature which argues that the group of people converges to a coordinated behavior over a long time (Bednar et al. 2010). The mathematical formulation of the model representing the peer pressure and the effects of interventions is explained below.

5.3.3.1 Effect of continuous peer pressure

For this particular case study, a clothing level of 1.0 to 1.3 is assumed as higher clothing level, 0.6 to 1.0, medium and 0.3 to 0.6, as lower. In the OBM, occupants with a higher clothing level are represented using a green color, while those with a medium clothing level are shown using an orange color and the lower level occupants are denoted using a red color. This is only for a representation purpose to help the users to visualize how occupants behave in the building when subjected to the dynamic building conditions. The peer pressure acts if there is an overlap between the connected occupants' clothing levels. An overlap means how distant is one's clothing level with the other connected occupant's clothing level (e.g., one occupant wearing a wool sweater versus another wearing a light cotton shirt). If this overlap is large, then that can result in an occupant influencing the connected occupant to change his/her preference. If the overlap is small, then the influence does not occur. In a real building scenario, this can be equivalent to a person who has a higher clothing level influencing other occupants to increase their clothing levels. Eq. 2 and Eq. 3 below shows the calculations involved in determining the new clothing level and the variability of each occupant after the peer pressure influence. Eq. 4 explains how the overlap is determined. Readers are encouraged to read Azar and Menassa (2013) for drawing more details about this logic.

$$c_j = c_j + \sigma \times \left(\left(\frac{h_{ij}}{v_i} - 1 \right) \times \left(c_i - c_j \right) \right) \tag{2}$$

$$v_j = v_j + \sigma \times \left(\left(\frac{h_{ij}}{v_i} - 1 \right) \times \left(v_i - v_j \right) \right) \tag{3}$$

Where,

c_j *is the clothing level of an occupant* j

c_i *is the clothing level of the connected occupant*

h_{ij} *is the overlap of clothing levels between the two connected occupants* $(Eq. 4)$

σ *is the peerincrement factor which denotes the effectiveness of the interaction*

v_j *is the variability of the clothing level of an occupant* j

v_i *is the variation of the clothing level of the connected occupant* i

$$h_{ij} = \min\left(c_i + v_i, c_j + v_j\right) - \max\left(c_i - v_i, c_j - v_j\right) \tag{4}$$

5.3.3.2 Effect of discrete energy based interventions

Another major factor that influences the occupants' behavior are the energy-based interventions. Common intervention methods adopted by the facility managers are education programs (posters, mobile based applications), monetary rewards. These interventions can occur at a different time step from the ES and in this case study, an intervention is planned at every 3 hours during the occupancy period (starting at 9.30 am). This is an important feature of the LABS framework wherein events can happen in the secondary program, at a different time step than the primary program and the framework has the capability to capture the effects of those actions as well. A typical energy intervention is assumed to influence the clothing levels of individual occupants. Random occupants are selected and if their clothing levels are less than 0.7 Clo, then their clothing level is modified by adding 0.2 Clo to their clothing level. This is analogous to occupants who have a less clothing level wearing an additional layer of clothing. ASHRAE Standard 55 for thermal environmental conditions for human occupancy (ASHRAE 2004) suggests that the clothing insulation provided by sweaters range from 0.13 Clo to 0.36 Clo and our assumption of adding 0.2 Clo to random occupants is thus reasonable.

Both the peer pressure and the interventions would be acting on the system simultaneously and this will be influencing the clothing levels of occupants continuously. At each time step (i.e., every one-hour), the major output variables that are decisive in calculating the PMV level are communicated from ES to the OBM. Based on this information and the clothing level and an assumed activity level, the PMV levels of all individual occupants are calculated separately. As mentioned before, the activity levels in an office will not change significantly and are considered at the default values available in the ES model which is 120 Met. The standard PMV calculation method given by ASHRAE standard 55 is adopted for calculating the PMV levels of each occupant.

Based on these PMV levels, the occupants are given an option to vote for a thermostat set point increase or decrease. The algorithm shown in Figure 5-7 depicts the methodology of determination of this voting. Here, *pmvOfOccupant* refers to the PMV value of a particular occupant. If the occupant is not comfortable (i.e., the PMV levels are less than -0.5 or greater than 0.5), the occupant would vote for a decision that makes them more comfortable. A vote of *"1"* means, the occupant desires to increase the thermostat temperature by 1 Degree Celsius and similar is the case with the other votes. Hence, based on the thermal sensation (PMV levels), the occupants make their thermal preferences (individual vote) and these preferences are used for calculating the change in thermostat set point to be made for each zone.

```
If (pmvOfOccupant <0.5 && pmvOfOccupant >-0.5)
       Vote=0;
Else if (pmvOfOccupant <-0.5 && pmvOfOccupant >-1.5)
       Vote=1;
Else if (pmvOfOccupant <-1.5 && pmvOfOccupant >-2.5)
       Vote=2;
Else if (pmvOfOccupant <-2.5 && pmvOfOccupant >=-3)
       Vote=3;
Else if (pmvOfOccupant >0.5 && pmvOfOccupant <1.5)
       Vote=-1;
Else if (pmvOfOccupant >1.5 && pmvOfOccupant <2.5)
       Vote=-2;
Else if (pmvOfOccupant >2.5 && pmvOfOccupant <=3)
       Vote=-3;
```

Figure 5-7 Algorithm that determines the occupant voting

An average vote is calculated for each zone and this average vote is used as a t_{offset} for calculating the new thermostat set point to be conveyed to the ES. Eq. 5 below shows the method through which this new thermostat set point is determined or a particular zone. S_{t+1} is the new set point and S_t is the old set point.

$$S_{t+1} = S_t + t_{offset} \tag{5}$$

5.3.4 Period 4: After regular office hours

After 5.00 pm, occupants are assumed to leave the office and similar to the phase 1, only the default thermostat schedule values are exchanged to EnergyPlus as there is no assumed occupancy. The coupled simulation will end by 12.00 pm i.e., at the 24th time step of ES (end of the day).

5.4 Scenario analysis and results

A scenario analysis is performed to demonstrate the capabilities of the LABS framework. In this scenario analysis, the ambient conditions of the building were investigated for its influence on people's comfort levels and an optimization is done for the thermostat set points of each zones. Three scenarios are performed on a typical day in the winter season and the analysis details are summarized in Table 5-4 below. The scenarios test the influence of the peer pressure and energy based interventions in a structured way. In scenario-1, only peer pressure among the occupants is assumed to be present in the building. This means that each occupant can influence their connected occupant's clothing levels. Each occupant is assumed to be connected with three other occupants in their zone. In scenario-2, the connectivity is increased to eight other occupants out of the total ten occupants in a zone. These two scenarios help in understanding the effects of connections between the occupants. Scenario-3 is scenario-2 combined with an additional energy intervention program occurring at every 3 hours in the building, starting from 9.30 am. In all the three scenarios, no connectivity is assumed between the zones, i.e., only the occupants within a zone interact.

Table 5-4 Description of the scenario analysis

Scenarios	Scenario Description
Scenario 1	Only peer pressure, with limited connectivity (3 out of 10 occupants)
Scenario 2	Peer pressure with high connectivity (8 out of 10 occupants)
Scenario 3	Peer pressure+ High connectivity + Interventions at every 3 hours, starting at 9.30 am

The effects of all these varied scenarios are plotted in Figure 5-8 and Figure 5-9 below for all the five zones. Figure 5-8 plots the thermostat set point variations (for all the three scenarios) whereas Figure 5-9 plots the corresponding clothing level variations. In Figure 5-8, the x-axis represents the occupancy hours starting from 8.00 am and the y-axis represents the thermostat set points in Degree Celsius. The blue bars show the default values of thermostat schedule (as per the assumptions of the default building model) while the colored lines in each graph shows the three scenarios as described in Table 5-4. Similarly, in Figure 5-9, the blue bars denote the default zone wise average clothing schedule (original model assumptions) and the three colored lines represent the variations in the clothing schedule as the day progresses. At 5.00 pm, occupants are assumed to leave the office and all the thermostat schedule settings goes back to the default values in the model and is hence not shown in these figures.

The immediate inference from the below figures is that occupants' response to the ambient conditions in the building is quite dynamic, and the default schedules and assumptions might not capture it in the best way possible. The wide variation that is visible across the scenarios is mainly due to the interaction dynamics between the occupants and the adaptive behavioral pattern that evolves due to this interaction. In some zones, the peer pressure among the occupants is working as an effective measure in allowing the people to adapt to a better clothing levels and hence vote for a lower thermostat set point level (for e.g., Zone-2). This can be well understood if this observation is correlated with the type of occupants in this particular zone.

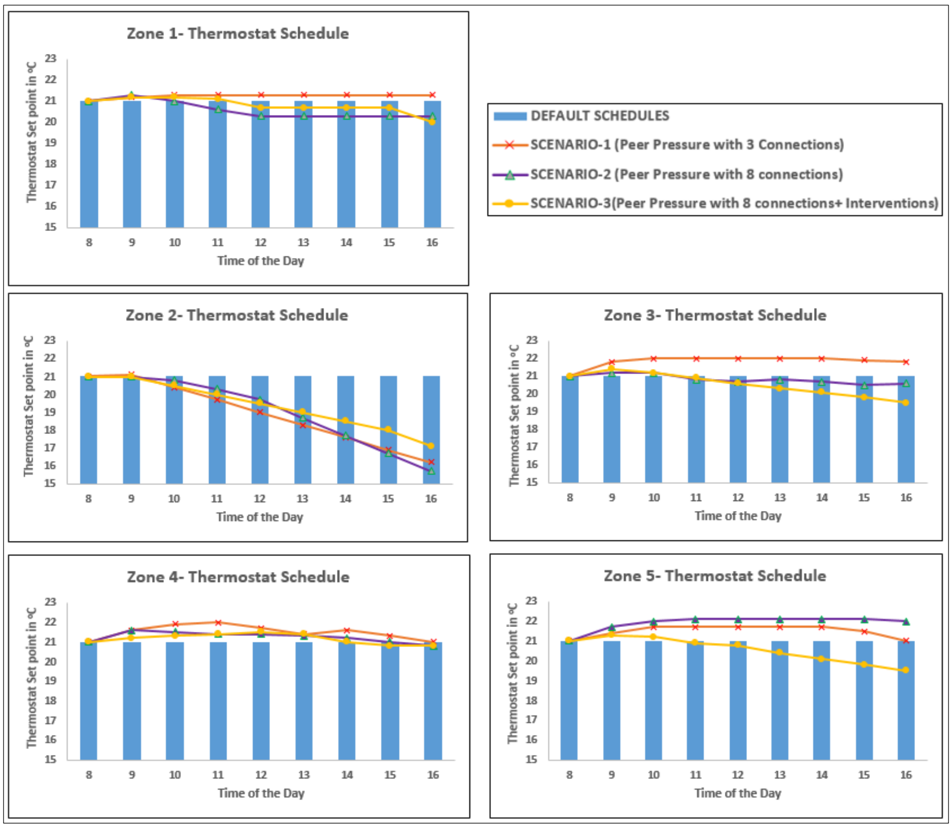

Figure 5-8 Thermostat schedule variations in the Five zones

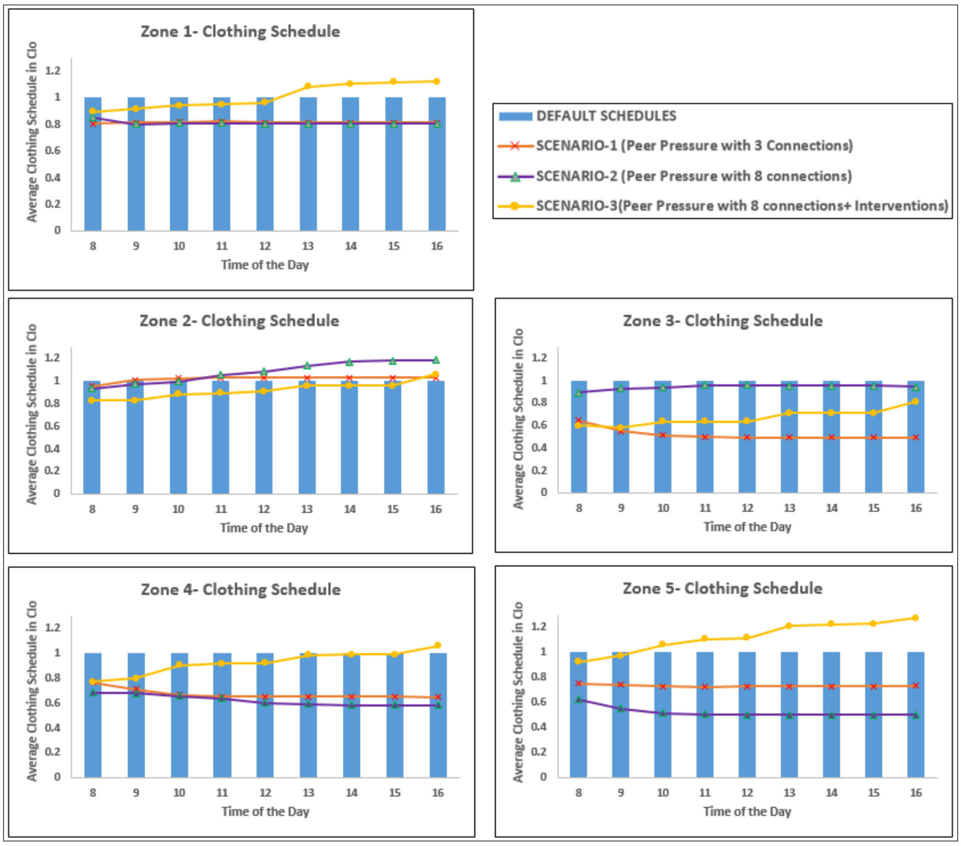

Figure 5-9 Clothing schedule variations in the Five Zones

Table 5-5 below contrasts the number of green, orange and the red occupants (the color codes given to occupants based on the clothing levels) at the start of the day with the end of the day. In zone-2, there is an increase in the number of green occupants by the end of the day and that is the reason why zone-2 has resulted in a reduced thermostat set points by the end of the day. This is quite analogous to the real-time operation of building wherein some zones or companies have more energy conscious occupants, who can also influence the energy use behavior of the other occupants. In a facility manager's perspective, this zone need not require an energy intervention program. In the other zones, an intervention based scheme comes out as a good measure.

Table 5-5 Occupant Mix at the start and the end of the Day

Zone	Color	**Scenario 1**		**Scenario 2**		**Scenario 3**	
		Start of the Day	End of the Day	Start of the Day	End of the Day	Start of the Day	End of the Day
Zone 1	Green	2	0	3	5	2	7
	Orange	7	8	5	0	5	2
	Red	1	2	2	5	3	1
Zone 2	Green	4	7	3	10	4	5
	Orange	5	0	7	0	3	5
	Red	1	3	0	0	3	0
Zone 3	Green	1	1	4	7	3	5
	Orange	4	0	5	1	5	3
	Red	5	9	1	2	2	2
Zone 4	Green	3	3	2	2	2	5
	Orange	4	0	2	0	7	1
	Red	3	7	6	8	1	4
Zone 5	Green	1	3	1	1	3	4
	Orange	7	2	4	0	4	5
	Red	2	5	5	9	3	1

This study assumed a simple rule for deciding the clothing level of the occupants (based on a uniform distribution and the chance of all clothing levels were the same) because representing the accurate behavior of occupants was out of scope of this paper. However, if we know about the behavioral trends in an office space, then this framework can be effectively used by the building practitioners to decide on the best strategy for a building's efficient maintenance and operation. In addition to the above analysis, the energy consumption of each scenario was recorded and is compared with the energy consumption of the default building model. The results are tabulated in Table 5-6 below. For the scenario-2 and the scenario-3 there is an energy savings compared to the base case. This means that more network connections between the occupants and appropriate intervention schemes can result in an energy savings. The energy savings obtained are less because this case study only analyzed the effects of variations in one factor i.e., the clothing level of occupants and its subsequent effects on the thermostat set point requirements. Even though some zones show a positive change (by reducing the set point requirements), the increase in the set points in the other zones neutralize these positive effects and make the energy requirements even.

Table 5-6 Energy savings of the framework with respect to the base case

Item	Base Case	Scenario 1	Scenario 2	Scenario 3
Electricity in kWh	204.57	204.57	204.57	204.57
Gas Use in kWh	345.82	357.55	339.96	337.03
Total Energy in kWh	550.39	562.12	544.53	541.60
Overall Energy Savings		**-2%**	**1%**	**2%**

From the above results and the Table 5-5 which showed the occupant mix for the tested scenarios, it is observed that the occupant mix at the start of the day has an effect in deciding the thermostat set points of a zone. In the OBM, this occupant mix was randomly generated and in order to test the sensitivity of this, several scenarios were conducted to gather an idea about how a varying occupant mix could influence the energy savings. The results obtained are provided in the Figure 5-10 below. The X-axis denotes typical simulation trial runs. The primary Y-axis plots the number of occupants against each color and the secondary Y-axis plots the corresponding energy savings. It can be clearly seen that as the number of green colored occupants at the start of a day increases, there is a significant effect to the energy savings. The main reason for the savings is the influence of green occupants in the building. Table 5-7 below shows the number of occupants at the start and end of the day, and the energy savings in each simulation run.

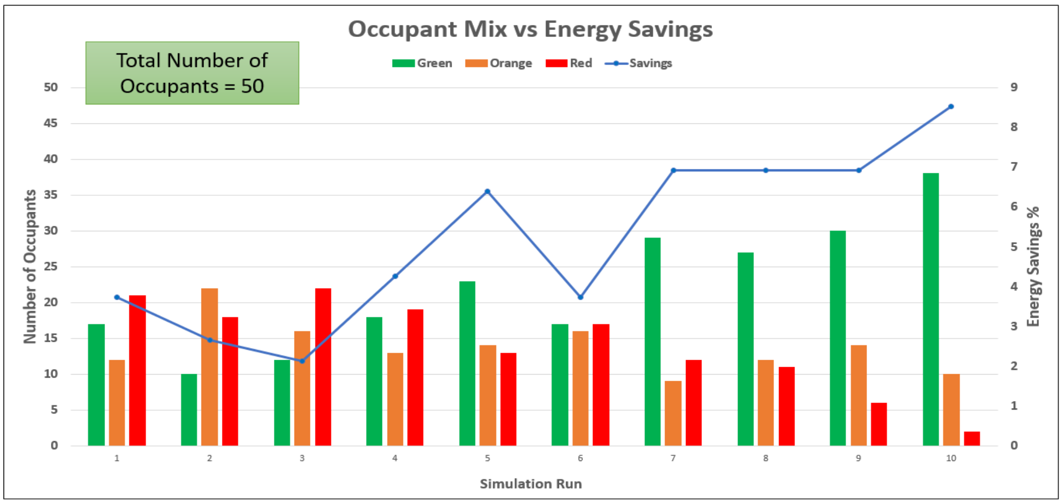

Figure 5-10 Sensitivity to the occupant mix

Table 5-7 Occupant mix and the corresponding energy savings

Simulation Run	Occupant Mix at the Start of the Day			Occupant Mix at the End of the Day			Energy Savings
	Green	Orange	Red	Green	Orange	Red	
1	17	12	21	25	13	12	4%
2	10	22	18	9	37	4	3%
3	12	16	22	18	21	11	2%
4	18	13	19	24	20	6	4%
5	23	14	13	28	18	4	6%
6	17	16	17	23	19	8	4%
7	29	9	12	33	16	1	7%
8	27	12	11	33	14	3	7%
9	30	14	6	39	8	3	7%
10	38	10	2	41	9	0	9%

These results are a clear indication that by controlling the behavioral traits of occupants (e.g., clothing adjustments, thermostat set point adjustments, heater and fan use, opening or closing windows), more energy savings is possible. As a continuation to this study, similar intervention programs can be designed in such a way to control the various other behavioral patterns of occupants (such as controlling the window opening or closing behavior, use of heaters and fans, use of other building appliances), thereby exploring the possibility of achieving more energy savings from a building's day-to-day operations. Given the flexibility of the LABS framework, such an analysis can be efficiently performed with much ease.

5.5 Conclusions- Phase 1c

The immediate impact of this study is that various building practitioners and expert facility managers can test various schemes and can decide on which scheme to adopt for ensuring better thermal comfort as well as ensuring maximum energy savings. The major feature of the LABS framework is in its flexibility to incorporate a wide array of simulation programs into the co-simulation loop. In the existing frameworks, either the connection framework itself has a steep learning curve (e.g., BCVTB, HLA) or the rules do not allow incorporating disparate simulation programs. The introduction of LCM in the LABS framework simplifies the message exchange process and shifts the connection sequence programing to the individual models, i.e., each program controls when to send and receive a message. By this way, LCM facilitates a direct connection across various simulation modules. This study also demonstrated how two programs runs in parallel across distributed workstations while exchanging the relevant data. These features of the LABS framework can help modelers and program designers in creating multiple simulation programs in distributed workstations and represent the complexities occurring within a system quite effectively. Given the fact that LCM is supported in Windows, Macintosh, and Linux platforms and building LCM in a computer is relatively straightforward, we believe that the ideas demonstrated through this paper will find applications in domains other than building energy simulation.

This study is not without limitations. This case study only analyzed the clothing level variations and its implications on determining the zone wise thermostat set points. There are several other behavioral adaptations occupants do such as opening or closing the windows, using personnel heaters and fans, which were outside the objectives of this study. In addition, the traditional PMV estimation has undergone many changes and there are many psychological and body related factors that also affect an occupant's comfort level. These were not considered as a primary focus of this study. Similarly, this framework has connected only two simulation programs across two workstations and represented only a small component in a building's operation. However, the LABS framework has the capability to scale up by connecting more simulation models and real time data sources to analyze a building's operation in its entirety. Furthermore, LCM can work across networks and we are currently incorporating these features as part of our ongoing study. In future work, the authors propose to use the LABS framework to include the above-mentioned points to result in a broader coupling of interdependent simulation processes in the building energy analysis domain.

In summary, the LABS framework has a relatively shallow learning curve, and can be easily mastered and implemented by various building practitioners, and the research professionals to create efficient and robust co-simulation systems. An appendix below describes the overall steps that can be followed for adopting the LABS framework to perform a distributed co-simulation process in the building energy analysis domain or any other related areas.

CHAPTER 6

Developing a Comprehensive Life Cycle Based System Dynamics Model

6.1 Summary

The previous three chapters outlined the importance of incorporating the effects of occupant's dynamic energy use behavior in energy simulation. Through this chapter, a comprehensive system dynamics framework is developed to analyze the effects of building materials and system performance on the energy performance of the building. This study adopts a life cycle based approach and has the capability to perform the energy simulation analysis by taking the building performance variations for the entire life cycle of the building. A detailed case study and validation of the model has also been presented as part of this chapter. This paper can also be found in Thomas et al. 2016b.

6.2 Life cycle based simulation approach

The overall approach adopted for achieving the objectives of this study is achieved by assimilating IEE, OE, REE and the EOLE into a SD simulation framework. SD is selected as the simulation technique owing to its strong capability in analyzing the inter-relationships and feedbacks existing within any complex system (Sterman 2000). The SD simulation method has been used in wide variety of applications including social sciences and in various engineering fields. Some of the civil engineering related studies include study about construction waste management (Li Hao et al. 2008), sustainable performance assessment of projects (Shen et al. 2005), building evacuation process (Thompson and Bank 2010) and project dispute resolution (Menassa and Pena-Mora 2010). Similarly, in the building sector, SD has been used in developing tools for studying energy policies and cost management and for energy efficiency during the building design process (Xing et al. 2013). No prior studies have utilized the capabilities of SD simulation in analyzing the dynamic building performance, different types of energy requirements in a building and the inter relationships existing between those energy requirements.

A causal loop diagram that explains the feedback and inter-dependencies existing in this system is shown in Figure 6-1 below. The relationships between different components are represented by means of a '+' or '-'sign. A '+' sign denotes that an increase or decrease of one variable brings a corresponding increase or decrease to the connected variable, respectively. Similarly, a '-'sign indicates an inverse relation with the connected variable.

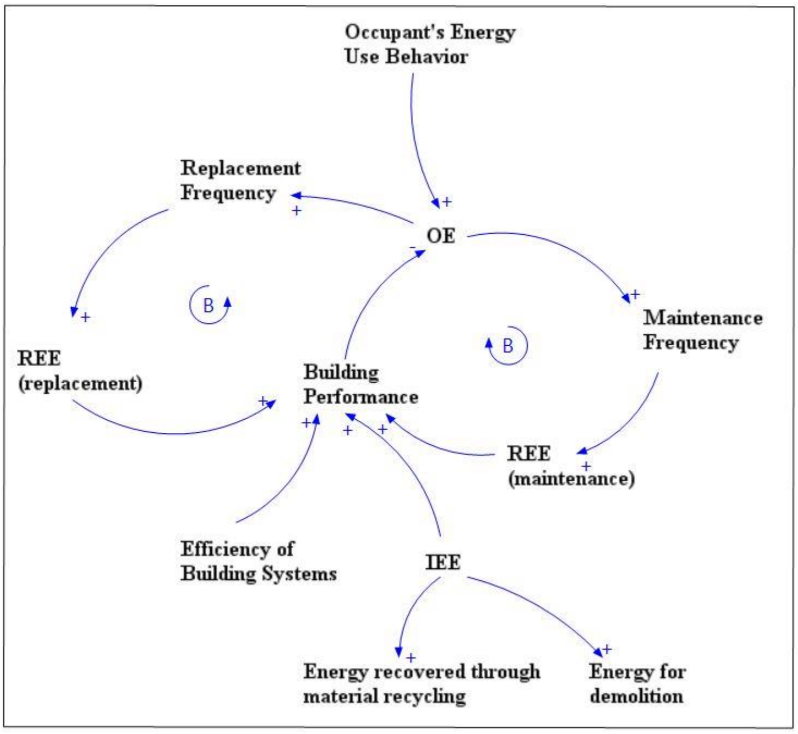

Figure 6-1 Causal loop diagram representing the interrelationships within system

For a high-performance building, the IEE spent will be higher compared to a normal building due to the provision of highly efficient systems, materials and various energy producing sources and technologies (e.g., solar panels, wind farms, passive lighting techniques, etc.). However, the advantage of providing highly efficient systems and materials will be visible during the use and maintenance phase in terms higher building energy performance. Another factor that can impact the building performance is the fluctuating efficiency patterns of various building systems (chillers and boilers, lighting systems, lighting appliances). Both these are represented using a '+' relationship with the building performance. If various systems, materials and equipment in the building performs well then that can result in reducing the operating energy requirements and vice versa. As obvious, this relationship is represented by means of a '-' relationship. Another major factor that can affect the OE consumption in a building is the dynamic occupant behavior (e.g., high energy consumers, medium energy consumers, low energy consumers) and is presented using a '+' relationship.

When the annual operating energy requirement goes up considerably, typically the building owners/facility managers adopt a more frequent maintenance and replacement schedule on various building materials. The impact of such a decision reflects immediately in terms of incurring REE for performing maintenance and replacement activities thereby increasing the overall building performance. Both these are represented by means of '+' relationships. Such an increased building performance results in bringing down the OE requirements and this acts as a continuous balancing feedback loop in this system. These two feedback loops are also represented in Figure 6-1 with typical SD conventions. During the end-of-life phase, the energy expended for demolition activities and the embodied energy that can be recovered back through recycling of materials are represented using a '+' relationship with the IEE. Occupant's energy use behavior is one other factor that affects the OE consumption, which is represented using a positive relationship. To analyze these relationships as outlined through the causal loop diagram and to achieve the earlier stated objectives, a methodology comprising of three phases is adopted.

6.3 Phase I: Defining dynamic building parameters

A building's energy requirements during its life cycle are affected by several factors. These factors include external environment related agents such as temperature, humidity, wind, light, pollutants, ultra violet rays, poor design and construction (Baumann 2009); as well as, internal factors such as energy use behavior of occupants, and efficiency of various building systems and assemblies. Empirical methods as well as computational models are created for analyzing energy use behavior of building occupants (Menassa et al. 2014, Azar and Menassa 2012, Masoso and Grobler 2010, Emery and Kippenhan 2006), the effect of various external agents and efficiency of building systems on the energy consumption (Rauf and Crawford 2014, Baumann 2009, Kesik et al. 2005) and various coupling frameworks for resulting energy efficient and environmentally sustainable building design. But, once the materials are put in place, it is not easy to determine how the materials deteriorate over its life cycle and the corresponding effects of this degradation on the operating energy requirements. This is still a nascent research area and hence considered as the exclusive focus of this study. There are several biological, chemical and physical processes causing ageing and deterioration of building materials (Harris 2001). Major reason for deterioration of building materials can be poor quality of materials, effect of external weather conditions, lack of a proper maintenance schedule, excessive usage etc. Various maintenance techniques are adopted by building owners to slow down the deterioration, thus resulting in an extended functional service for the component (Grant et al. 2014). Some of the commonly observed deterioration patterns are discussed by various studies.

Sohet et al. (2002) analyzed various cementitious, synthetic and ceramic mosaic cladding materials used in building's façade, and found out that they primarily follow a linear or exponential deterioration pattern and predicted the service life based on those identified deterioration patterns. Linear deterioration pattern was hypothesized to occur when the material is subjected to the influence of a single agent while an exponential deterioration occurs when multiple agents cause the material to degrade. Sohet et al. (2002) collected actual performance data of external cladding from buildings of various age and proposed that when the performance of the material is at 40% to its initial value, then the material can be considered to have reached the end of its useful service life. Other major studies used Semi-Markov approach and Weibull probability distribution to predict the service life and deterioration trend for various building materials (Maranno et al. 2010, Grussing et al. 2006, Garavaglia et al. 2000). These approaches are widely used in asset management to estimate the expected service life of the materials. Of which, the patented study by Marranno et al. (2010) used the Weibull distribution to propose a polynomial shaped deterioration pattern for building materials with maintenance and replacement affecting the material condition. This study used this trend based on an initial probabilistic deterioration pattern refined by real material condition data. Similarly, Keisk et al. (2005), Gaspar et al. (2005) and Harris (2001) also adopted a polynomial deterioration pattern to represent the deterioration of building materials.

In the absence of a large pool of studies analyzing the actual deterioration patterns of building materials, the authors believe that the general trends as suggested through the above-mentioned studies (linear, exponential and polynomial) fairly represent the degradation patterns of most of the materials. Since the major focus of this study is to model the effect of material deterioration on the energy requirements, factors affecting the material deterioration and randomness involved in the actual material deterioration trends is outside the current scope of this study. To generate the material performance curves, the concept proposed by Sohet et al. (2002) is adopted. During the building life cycle, all materials are assumed to deteriorate from 100% (installed level) to k% (end of service life for that material). The value of *'k'* denotes the worst level of a material's performance when replacement of that material becomes a necessity. Figure 6-2 below shows typical performance variation curves generated using this concept for polynomial, linear and exponential deterioration patterns. In the equations, *'y'* denotes to the material performance level in percent and *'x'* denotes material lifetime in years and the coefficients A, B, C, D and E are numerical constants in the equation. The curves shown below represent a general scenario assuming no maintenance is performed on the material during the entire service life.

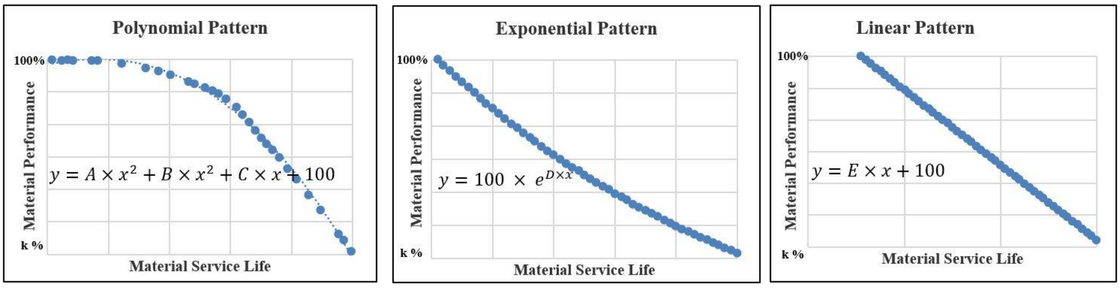

Figure 6-2 Typical material deterioration patterns

6.4 Phase II: Developing system dynamics simulation framework

The coupling framework adopted for this study is presented in Figure 6-3 below. The main components of this framework are the SD simulation model developed in Anylogic V. 7.0.0- a java based multi-method simulation tool, LCA repository developed in Microsoft Excel 2013 and the building energy simulations performed using EnergyPlus V 7.2. The LCA repository contains the EE intensity values for different building materials and the IEE intensity for various types of office buildings. EnergyPlus simulations are performed for calculating the overall electricity and natural gas energy requirements (calculated in Giga Joules) for various building performance levels.

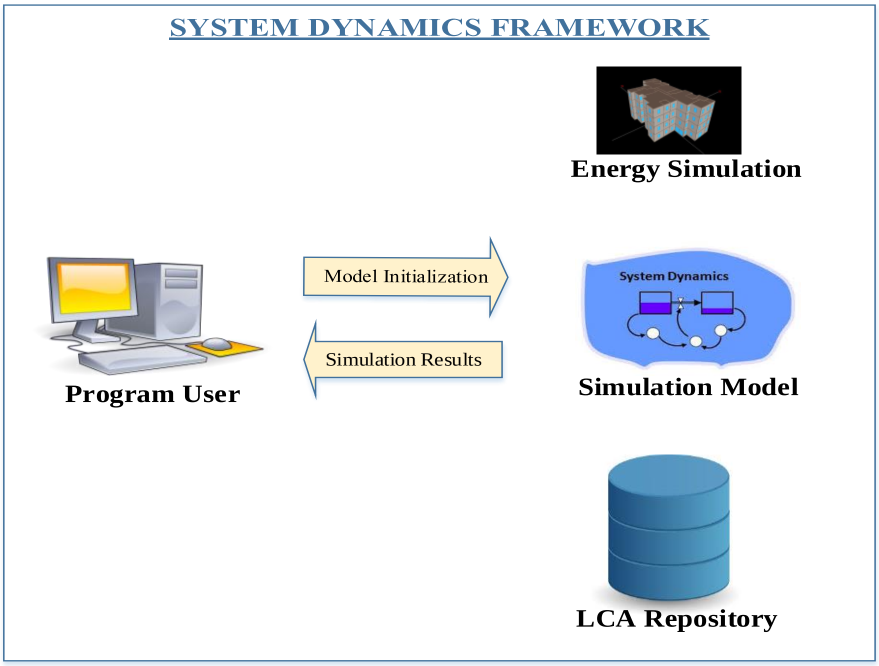

Figure 6-3 Coupling simulation framework

The initial step of one typical simulation run is initializing the model with the assumptions such as the simulation period (for e.g., 50 years, 75 years etc.), material deterioration pattern and initial material maintenance frequency. Initial material maintenance frequency refers to the typical frequency in which maintenance is conducted on the material assembly. Typically, this information is obtained from the building maintenance and operation manual or is followed based on various building maintenance standards. Maintenance is a routine process where a systematic evaluation and preventive maintenance are performed wherever necessary as assessed by the facility manager. For instance, a value of 15 means a building stakeholder intends to perform a preventive maintenance on the building every 15 years; i.e., at 15th year, 30th year, 45th year and so on. The maintenance frequency usually depends on several factors such as building location; type of building, extent of usage etc. and this frequency can be different for different assemblies. For instance, a good maintenance frequency for various external envelope materials is between 5-20 years (Athena 2002).

Once the model is initialized, one run of the simulation can be performed. The overall logic adopted for one such run is summarized in Figure 6-4 below. At time=0, IEE is incurred for constructing the building. Subsequently during the use and maintenance phase, OE is incurred in the form of electricity and gas usage and REE is incurred because performing a maintenance or replacement activity. The OE requirements are calculated based on the building energy simulations and the EE information is computed by exchanging information with LCA data repository. The frequent maintenance and replacement of materials by incurring a REE improves the building performance and acts as a feedback that impacts the OE consumption. This feedback is represented using a dash line in Figure 6-4. When the building reach the end-of-life phase, the energy incurred for demolition and the EE that can be recovered back through material recycling are computed.

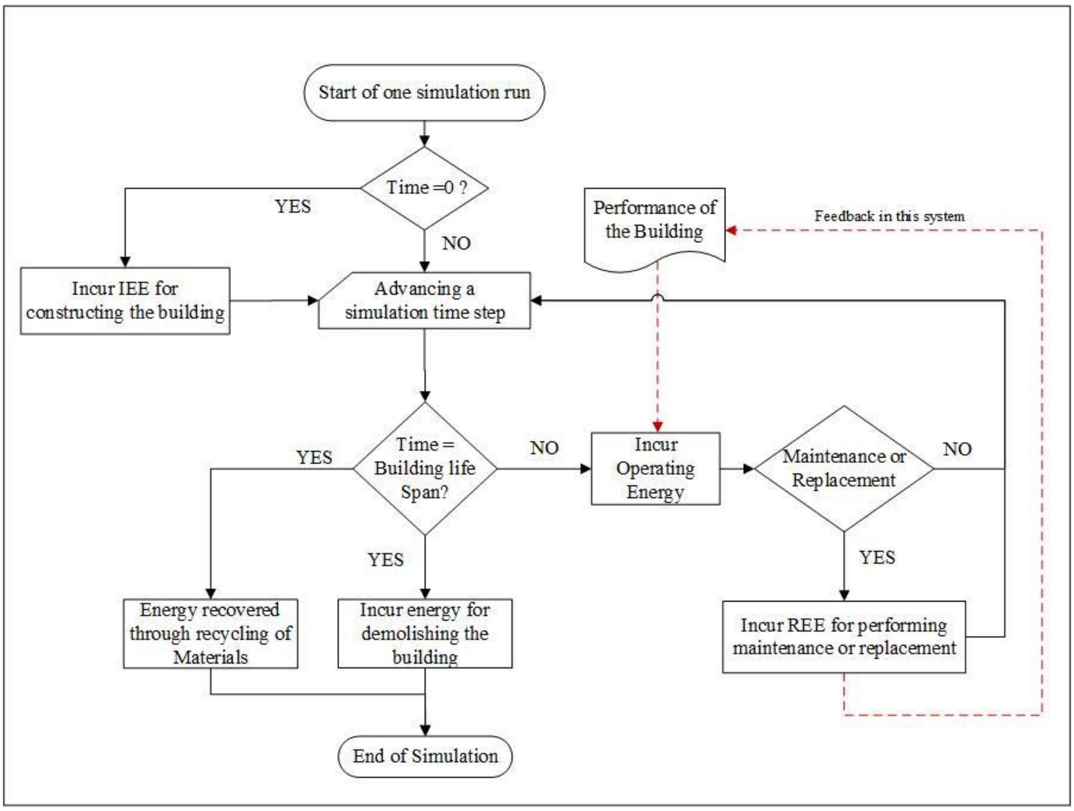

Figure 6-4 Logic adopted for the SD simulation

The simulation logic outlined above (Figure 6-4) is executed through the SD model shown in Figure 6-5 below. Various components in this SD model include stock, flow, parameters, dynamic variables, java variable (for storing values during the simulation) and a java function (for executing additional programming script). A detailed explanation of various inter-relationships and the feedback existing in this system are provided in a phase-wise manner below.

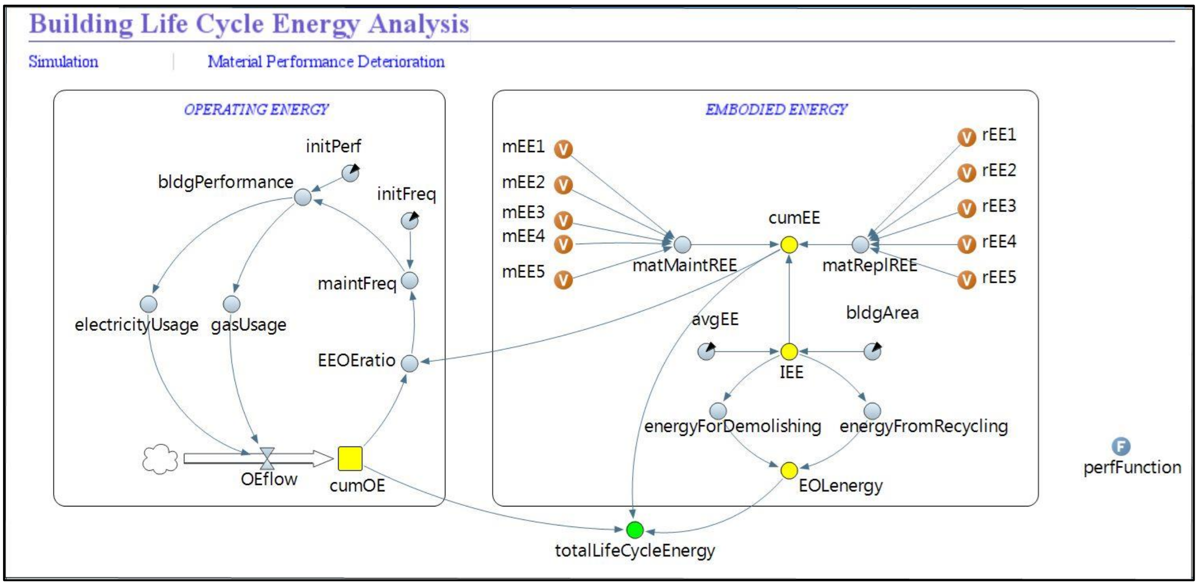

Figure 6-5 System dynamics model

For the material production and construction phase, several studies have estimated the IEE for buildings across different geographic locations (Rauf and Crawford 2014, Crawford et al. 2010, Jackson 2005, Fay et al. 2000, Treloar et al. 2000, Cole and Kernan 1996). The IEE per unit area suggested by all these studies varied considerably mainly because of the different geographic locations and boundaries assumed in the LCA analysis. Due to this wide variation and to adopt a best possible unit value that represents a general building scenario, an average value across all these studies is assumed and is calculated in the LCA repository. *'avgEE'* is a parameter in the model that represents the average IEE per unit area. *'IEE',* is a dynamic variable that is used for calculating the IEE for the building under consideration and is determined based on Eq. (1) given below when time=0.

$$IEE = avgEE \times bldgArea \tag{1}$$

The OE requirements during the use and maintenance phase consist of electricity and natural gas. Typical energy simulation programs (including EnergyPlus) perform simulation for a maximum time frame of one year and currently do not possess the capability of predicting the OE consumption for the entire life cycle accounting for the effect of dynamic building performance on the energy usage. To mitigate this, for this study, energy simulations for various building performance scenarios are conducted beforehand. From this analysis, a best-fit equation is developed that can provide the electricity and gas energy requirements with acceptable accuracy. The equations thus developed are used in the SD model for simulating the electricity and gas usage based on the building performance level dynamically generated by the model. This approach is adopted presently since the SD simulation inherently does not allow coupling with other simulation programs unless the user employs distributed simulation frameworks such as the High-Level Architecture (HLA), Building Control Virtual Test Bed (BCVTB) or a similar middleware that incorporate inter-operability aspects. This is not in the scope of this present research and the authors are considering this aspect to be incorporated in their future research.

6.4.1 Estimation of individual material performance and overall building performance

The performance level of a building at any time instant is calculated based on the performance of its individual materials. Figure 6-6 below illustrates the procedure adopted for obtaining the performance variation pattern of a typical material. *'Mat1P'* is a dynamic variable that represents the performance of a single material at a time instant. This performance value is expressed as a percentage and is generated based on the values of *'detPattern'*, *'cumMaintPer1'* and *replYear1'* at every time step. The parameter *'detPattern'* refers to the pattern of deterioration that is inputted by the user during the model initialization process. A maintenance performed on a material improves the performance of a material and the amount of maintenance performed typically depends upon the condition of the material in the building. A parameter *'cumMaintPer1'* is used in the model to represent the cumulative maintenance performed on the material under consideration during its useful service life. When the performance of the material falls below k% (Refer Figure 6-2), the material is assumed to have reached its end of useful service life thus requiring a replacement. The parameter *'replYear1'* takes the value of the specific time step in which this replacement of material is to be conducted. Once the material is replaced, the value of '*cumMaintPer1*' will be set to zero for the new cycle. This value is generated within the system based on the original replacement period and the service life extended due to regular maintenance. Both *'cumMaintPer1'* and *replYear1'* are computed based on the above-mentioned logic which is executed by means of programming scripts written in a function *'perFunction'* within the SD model.

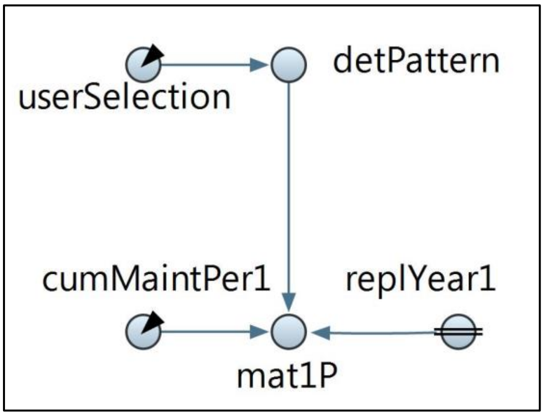

Figure 6-6 Material performance calculation

Eq. (2), Eq. (3) and Eq. (4) below show typical equations generated for exponential, polynomial and linear deterioration pattern computing the value of *'mat1P'* at any time instant. In these equations, 't' refers to the age of a material and the coefficients A, B, C, D and E denotes numeric values that vary for different material service lives. These equations are developed for a typical material based on the patterns discussed earlier (Keisk et al. 2005, Sohet et al. 2002, Harris 2001) and similar equations are generated for all materials in the material assemblies being analyzed.

$$mat1P = 100\times e^{(A\times t - replYear1)} + cumMaintPer1 \tag{2}$$

$$mat1P = -B\times(t - replyear1)^3 - C\times(t - replyear1)^2 + D\times(t - replyear1) + cumMaintPer1 \tag{3}$$

$$mat1P = -E\times(t - replyear1) + 100 + cumMaintPer1 \tag{4}$$

From the performance curves thus generated for individual materials, the overall performance of the material assembly is computed by allocating appropriate weights for each material in the assembly. The overall building performance (*'bldgPerformance')* thus generated is used to estimate the OE requirements, *'electricityUsage'* and *'gasUsage'* using the best-fit equations discussed in the earlier section. The operating energy thus incurred at each time instant, *'OEflow'* is calculated by summing up the electricity and gas requirements for the building. *'OEflow'* decides the rate of increase of the stock *'cumOE'*. Otherwise stated, at each time instant, the operating energy requirements are calculated and accumulated to a stock that represents the cumulative operating energy usage in the building.

6.4.2 System dynamics feedback loop affecting the operation energy

The feedback loop in this system dynamically controls the frequency of maintenance performed in the building. Usually, a building stakeholder carries out a maintenance based on inspecting buildings' overall performance level, operating energy consumption, and the overall costs for the maintenance activity. For instance, when the cumulative OE use is increasing considerably, building stakeholder might consider performing more maintenance on the building to improve the building performance and keep the operating energy consumption within controllable limits. This concept is represented by using a dynamic variable *'EEOEratio',* which calculates the ratio of cumulative EE and the OE at every time instant. During the initial years of a buildings' life cycle, this ratio will be more than unity as the major energy investment in this period consists of IEE. At later phases, the OE increases and at a certain break-even point this ratio will go below unity, which means that the cumulative OE has gone past the cumulative EE invested for constructing and maintaining the building. This is the point where frequent maintenance is required for keeping the building performance and operating energy consumption under control. The maintenance frequency, *'maintFreq'* is computed based on the values of *'EEOEratio'*.

It is assumed that whenever the ratio between EE and the OE reduces by 10%, the maintenance frequency is reduced by one year from the maintenance frequency entered by the user while initializing the model. This hypothesis is put forward by the authors to represent the real material maintenance and replacement process in a buildings' life cycle as close as possible and in the absence of prior studies that dealt a similar concept. The usual practice followed in any building is that when the building becomes older, the requirement for the material maintenance increases to keep the building's performance under control. This dynamic building performance triggered by the material maintenance or replacement will in turn decide the operating energy requirements of the building. This represents one complete feedback loop in this system.

6.4.3 Recurrent embodied energy estimation

The REE incurred for performing maintenance during the maintenance year depends solely on the performance level of the material. The amount of energy to be spent for each maintenance activity will be based on the type of maintenance (major, minor or no maintenance) required. A study carried out by Venta and Eng (2001) observed that around 5% to 10% of the material needs to be replaced during a typical maintenance activity of building envelope materials. Inspired from this study and to show the significance of maintenance on the building energy consumption, an increase of 7% to 10% of performance of a material in the assembly is assumed as a major maintenance while any increase in the performance less than 7% is considered as a minor maintenance. When the performance of the material is above 95% no maintenance is assumed, which is typically the case in a building. Maranno et al. (2010) and Grussing et al. (2006) also described a similar step function increase in the building material performance. Based on this increase in material performance (computed using a uniform random distribution), *'mEE1'*, a java variable is used to calculate the EE incurred for the corresponding maintenance activity using the EE intensity values exchanged from the LCA repository. By adopting the same method, the EE incurred for performing the maintenance of any number of materials under analysis can be estimated. When the performance of the material is above 70% and below 95%, a minor maintenance (an increase of performance less than 7%) is assumed. When the performance of the material is between 40% and 70% (material is nearing the end of service life), it is assumed that a major maintenance (an increase in performance within 7% to 10%) is desirable.

A similar methodology is adopted for estimating the REE incurred during the material replacement process. The variables *'cumMaintPer1'* and *'replyear1'* are both used for generating the material performance pattern (Figure 6-6) and *'rEE1'* is a java variable used in the model (Figure 6-5) for storing the EE incurred for the replacement activity of an individual material. This approach also can be extended to generate the performance and to calculate the EE for replacement for any number of materials. The EE thus obtained for maintenance and replacement activities for all the materials are summed up in the dynamic variable *'matMaintREE'* and *'matReplREE'*. Finally, cumulative embodied energy is calculated by adding the REE with the IEE based on Eq. 5 given below.

$$cumEE = IEE + matMaintREE + matReplREE \tag{5}$$

The end-of–life phase consists of the energy required for demolishing the building and the embodied energy that can be recovered through recycling. Prior studies estimated that, energy required for demolishing can be up to 5% of the IEE and the embodied energy that can be recovered back can be around 12% of the IEE (Thormark et al. 2006, 2002, Crowther et al. 1999, Suzuki et al. 1998). The dynamic variables '*energyForDemolishing'* and *'energyFromRecycling'* are calculated at the end of buildings' lifespan from IEE. Based on these two dynamic variables, *'EOLenergy'* calculate the energy requirement from the end-of life phase. All energy requirements are added to the variable *'totalLifeCycleEnergy'* and at any time instant the value in this dynamic variable provides the total energy requirements for the building.

Table 6-1 below summarizes the typical inputs and outputs from the main components of this framework. Subsequent sections describe a case study followed by discussing the results and conclusions.

Table 6-1 Framework- Inputs and Outputs

Item	Input	Output
SD Simulation	Building life expectancy in years, Material deterioration pattern, Initial maintenance frequency	IEE, OE, REE, EOLE
EnergyPlus Simulation	Dynamic building performance parameters	Electrical energy and natural gas consumption
LCA Database	Building gross area, quantity of building materials	EE required for producing a given quantity of the building material

6.5 Phase III: Model validation

The system dynamics framework developed in this study addresses the global objective of understanding the effect of material degradation on the energy requirements by visualizing the inter-relationships that exist between different energy requirements. However, the existing literature in this domain is limited only to a few case studies that only dealt with the deterioration patterns of only few materials. Once the material is put in place, as opined by the industrial experts, it is hard to track its actual performance and plot a deterioration pattern while the building is under the operation. Visual inspection is the usually adopted method for measuring the actual performance, but it is limited only to the externally visible material systems. Another method that is adopted recently is the thermography-based method for studying the actual thermal resistance of insulation materials at a given point in time (Ham and Golparvar-Fard 2015, 2014). This study does not however provide a history of deterioration to allow for life cycle analysis. For adopting detailed validation technologies such as historical validation or multistage validation (Sargent 2000), the major pre-requisite is the availability of enough data points (in this case, the actual performance of various building materials).

In lieu of the above-mentioned facts and considering that this research domain (the dynamic effect of material deterioration on the energy consumption) is still a nascent area, validation adopted in this paper is limited to technical validation, i.e., focusing on the technical and computing aspects of the model. Sargent (2000) proposed" Parameter Variability–Sensitivity Analysis" for performing a technical validation of the model and this method is widely adopted by various prior studies (Azar and Menassa 2015, 2012, Wang et al. 2012, Sellers 2004) to understand the sensitivity of a simulation model to different input parameters. The next section presents through a case study, the scenario analysis performed on the model to illustrate the potential impact of material deterioration on the building energy consumption.

6.6 Case study

Different building systems or assemblies have varying effects on the energy requirements of a building and this general framework can be easily applied to study the effects of degradation of various building systems/assembly. An office building located in Chicago is selected as the case study to demonstrate the capabilities of the framework. This building model is one of the EnergyPlus compatible models provided by the Department of

Energy across different climate zones in the U.S. (DOE 2015). Table 6-2 below summarizes some of the major building characteristics.

Table 6-2 Characteristics of the case study building

Item	**Description**
Location	Chicago
Type	Office
Latitude	41.77 degree
Longitude	-87.75 degree
Shape	Rectangle
Building length	73.11 m
Building width	48.74 m
No of stories	12 story plus basement
Gross area	46, 320 sq. m
Window-to-Wall ratio	38, Equal distribution of windows
Number of zones	19
Number of total Occupants	2,397
Occupancy Schedule	**Weekdays:** Occupancy considered from morning 7.00 am to 10.00 pm *(95% occupancy from 8.00 am to 12.00 pm and 1.00 pm to 5.00 pm.)* **Saturdays:** Reduced occupancy than normal weekdays **Sundays:** No occupancy considered

Presently, the framework is designed to simulate the effects of deterioration of any five major materials in any building assembly. In a building's external wall envelope, the five major materials are the windows, wall insulation, wall material (e.g., concrete, wood), external cladding (e.g., stucco, brick), and internal finish (gypsum, concrete). In a similar way, the effect of the insulating properties of other building envelopes such as roof assembly, floor assembly, effects of dynamic efficiency pattern of mechanical systems such as boilers, chillers, and air handling units etc. can also be analyzed using the existing model. For analyzing different assemblies, the only small addition to be made is with regards to the operating energy equations. Since the authors are developing the real-time coupled version, the current stage of the framework demands manual input of the best-fit equations (for the material assembly under consideration) to generate the OE in the model. Once the full coupling is achieved, this framework will have seamless integration capabilities to analyze the effects of any identified factor (degradation of external wall/roof/floor envelope, dynamic efficiency pattern of building HVAC components etc.) on the OE and the REE performance of the building. For this study, degradation of the insulation capabilities of the external wall assembly (consisting of external walls and windows) is considered.

The deterioration patterns of all five materials were derived based on the manufacturers recommended service life and the earlier discussed deterioration patterns. For instance, typically the recommended replacement period for windows is 30 years (NREL 2015), wall insulation and wall concrete is building's lifetime (RSMeans 2014), around 15 years for the external stucco cladding (Sohet et al. 2002) and 25 years for internal gypsum finishing (Crawford 2010). If no maintenance is performed on the material, then it is assumed that the material needs to be replaced at these manufacture's recommended warranty period. Maintenance performed on the material (minor or major) increase the performance of the materials thereby extending the service life. The frequency at which maintenance is performed on an external wall and windows depend upon various factors such as building location and type, extent of usage etc. General items addressed during a maintenance period are fixing cracks, defects and leaks and reinstating some of the damaged components. Even though in most cases visual inspection is enough for assessing the extent of maintenance, some scenarios demand detailed investigation methods such as sample extraction, standard water penetration testing (ASTM E1105-15) and air infiltration tests (ASTM E783 - 02). In the case of maintenance on insulation material, the usual practice as confirmed by the industrial experts would be to add new insulation material to increase the overall insulation level and maintain the provisions as stipulated by the various codes and standards (e.g., ASHRAE 2013, DOE 2012, IECC 2009).

A material's insulating performance is usually expressed in terms of R-value. ASHRAE 90.1-2013 defines the R-value as the "reciprocal of the time rate of heat flow through a unit area induced by a unit temperature difference between two defined surfaces of the material or construction under steady state conditions". With age, the appearance and the various material properties (for e.g., R-value) degrade thereby bringing down the performance of the individual material and the overall building performance (Ham and Golparvar-Fard 2015, 2014, Sohet et al. 2002). Several standards provide the recommended minimum insulation level of various building materials (ASHRAE 2013, DOE 2012, IECC 2009) for the building owners and stakeholders to follow.

6.6.1 R-value and weighing scheme estimation

To find out the effect of each material in the assembly, an appropriate weighing scheme is defined. The weight for an individual material in this case is determined based on its insulation capability, (i.e., R-value) and its overall contribution to the overall insulation properties of the assembly. EnergyPlus does not directly provide the R-values of materials. For windows the U-value is provided (R-value can be found out as the inverse of U-value). For other materials, the R-values need to be calculated from the thermal conductivity and thickness values, which are available as part of the case study building model. The initial R-values thus calculated and the weights derived are provided in Table 6-3 below. To exclusively study the performance variation pattern of a specific material assembly, the overall weighted performance calculated for the external envelope assembly is assumed as the overall building performance itself in this study as the performance of all other material assemblies and systems are assumed to be remaining constant.

Table 6-3 R- value estimation for individual materials

A	B	C	D	E = D/C	F = 1/ E	G
Assembly	**Material**	**Material Thickness (m)**	**Thermal Conductivity (W/m-K)**	**U-value (W/m2-K)**	**R-value (m2-K/w)**	**Weight (In %)**
Exterior Envelope	1 IN Stucco	0.03	0.69	27.34	0.0366	1.9
	Mass Non-Res Wall insulation	0.07	0.05	0.75	1.3377	70.1
	8IN Concrete HW	0.20	1.31	6.45	0.1550	8.1
	1/2 IN Gypsum	0.01	0.16	12.60	0.0794	4.1
	Non-Res Fixed Assembly Window	-	-	3.35	0.2985	15.6

6.6.2 Estimation of overall R-value of the assembly

The four different wall materials (exterior cladding, concrete wall material, insulation and interior finishing) are placed one over the other (i.e., connected in series), while the windows are connected in parallel with the wall. The presence of a highly conductive material sandwiched in parallel can result in thermal bridging thereby reducing the overall R-value of the assembly. Summing up in series and summing up in parallel principles outlined by the sustainability workshop (Autodesk 2015) are used for finding out the overall R-value. The R-value of the external wall materials sandwiched together is found out by summing up in series. From the R-values, the U-values are estimated as the reciprocal of R-value. From the individual U-values, the total U-values are computed based on the percentages of windows and wall in the assembly considered. For this model, the ratio of windows in the assembly is 38% and consequently the ratio of walls in the assembly is 62%. Based on this information and as per a previous study that estimated the U-values of wall assembly (Taitem, Inc. 2008), the total U-value and corresponding R-value is calculated as summarized in Table 6-4 below.

Table 6-4 Effective R-value calculation for material assembly

	Material	R-values (m2-K/w)	R- value Sum (m2-K/w)	U-value (W/m2-K)	Total U-value (W/m2-K)	Overall R-Value (m2-K/w)
A	1 IN Stucco	0.037	1.609	0.622	1.658 *(A × 0.62+ B × 0.38)*	0.603
	Mass Non-Res Wall insulation	1.338				
	8IN Concrete HW	0.155				
	1/2 IN Gypsum	0.079				
B	Non-Res Fixed Assembly Window	0.299	0.299	3.350		

6.6.3 Electrical and gas energy consumption

As mentioned in the methodology section, numerous simulations with varied building performance levels (varied R-value levels for the external wall and window assembly) are performed in EnergyPlus to develop generalized equations for simulating the electricity and gas consumption. The graphs and equation thus obtained by plotting the simulated energy requirements of different building performance levels are shown in Figure 6-7 below. To perform an extra level of validation of the case study building model, the simulated OE requirements of the base case study model are compared with the real average OE information of similar sized office buildings from the City of Chicago database for the year 2014. This online database provides the actual OE consumption details of different types of buildings and 18 office buildings of comparable size (~40,000 sq. m to ~50, 000 sq. m.) of that of the actual case study model (46, 320sq. m.) are selected for the comparison. The average annual operating energy of these 18 buildings differ by only around 6.5% with the simulated energy requirements of the case study building model. This provides a reasonably strong validation for the building model selected as the case study.

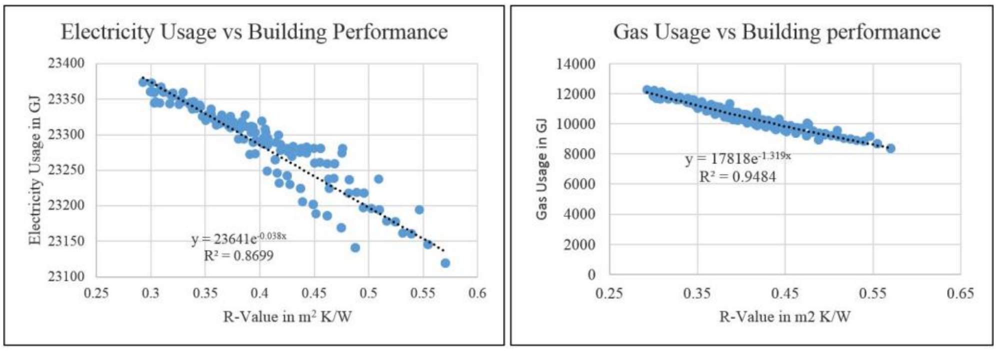

Figure 6-7 Generalized equation for electricity usage and gas usage

6.6.4 Sensitivity analysis

Various scenarios performed are summarized in Table 6-5 below. For each deterioration pattern, the sensitivity to different initial maintenance frequencies is analyzed. Sohet et al. (2002) considered a 40% performance of cladding materials as the worst performance level and in this study also a performance level of 40% is adopted as the value for k. The base case assumes that no regular maintenance is performed on the building during its entire life cycle. However, when the material reaches its end of service life (40% of initial R-value), the material is assumed to be requiring a replacement with a new material. The energy requirements during each phase of the life cycle (IEE, OE, REE and EOLE) of each scenario are computed and represented in GJ for easy comparison.

Table 6-5 Sensitivity analysis performed

Deterioration Pattern	Initial Maintenance Frequency (Years)
Linear	Base Case (No Maintenance)
	20
	18
	15
	13
	10
Exponential	Base Case (No Maintenance)
	20
	18
	15
	13
	10
Polynomial	Base Case (No Maintenance)
	20
	18
	15
	13
	10

6.6.5 Results of scenario analysis

Across various scenarios, it is assumed that IEE remains constant (otherwise stated, same building with different maintenance frequency) to exclusively study the relationship between OE and REE. The results obtained for each deterioration pattern are given in Table 6-6, Table 6-7, Table 6-8 below. Initial maintenance frequency in the table refers to the maintenance frequency entered by the program user initially. Final maintenance frequency is generated by the feedback loop after one simulation run. Different energy requirements are then recorded for each simulation run and the energy savings possible in each scenario are determined based on the base scenario. The *"OE savings"* is obtained by subtracting the cumulative OE of the scenario under consideration from the cumulative OE value of the base case. The results indicate that all scenarios that performed maintenance have resulted in savings in OE. Similarly, *"Additional REE"* of a scenario refers to the additional EE spent exclusively for performing the maintenance on the materials. The *"NetSavings"* is then calculated by subtracting the *"Additional REE"* from the *"OE Savings"*.

Table 6-6 Scenario analysis summary - Exponential deterioration pattern

Exponential Deterioration Pattern										
IMF (Years)	**FMF (Years)**	**IEE (GJ)**	**OE (GJ)**	**REE (GJ)**	**EOLE (GJ)**	**Total Energy (GJ)**	**OE savings (GJ)**	**Additional REE (GJ)**	**Net Savings (GJ)**	**Net Savings in %**
0	0	524,451	1,692,536	15,676	(36,712)	2,195,952				
20	16	524,451	1,676,518	10,585	(36,712)	2,174,842	16,019	(5,092)	21,111	9.7%
18	14	524,451	1,679,646	18,368	(36,712)	2,185,753	12,891	2,692	10,199	4.7%
15	11	524,451	1,660,474	10,134	(36,712)	2,158,347	32,062	(5,543)	37,605	17.2%
13	9	524,451	1,651,043	12,341	(36,712)	2,151,124	41,493	(3,335)	44,828	20.5%
10	6	524,451	1,655,051	14,788	(36,712)	2,157,578	37,485	(889)	38,374	17.6%

Note: IMF = Initial Maintenance Frequency; FMF= Final Maintenance Frequency.

Table 6-7 Scenario analysis summary - Polynomial deterioration pattern

Polynomial Deterioration Pattern										
IMF (Years)	**FMF (Years)**	**IEE (GJ)**	**OE (GJ)**	**REE (GJ)**	**EOLE (GJ)**	**Total Energy (GJ)**	**OE savings (GJ)**	**Additional REE (GJ)**	**Net Savings (GJ)**	**Net Savings in %**
0	0	524,451	1,623,272	15,676	(36,712)	2,126,688				
20	16	524,451	1,611,790	21,627	(36,712)	2,121,157	11,482	5,951	5,531	2.6%
18	14	524,451	1,607,037	20,262	(36,712)	2,115,039	16,235	4,586	11,649	5.6%
15	11	524,451	1,605,963	20,435	(36,712)	2,114,137	17,309	4,758	12,550	6.0%
13	9	524,451	1,615,689	18,046	(36,712)	2,121,475	7,583	2,370	5,213	2.5%
10	6	524,451	1,605,488	25,730	(36,712)	2,118,958	17,783	10,053	7,730	3.7%

Note: IMF = Initial Maintenance Frequency; FMF= Final Maintenance Frequency.

Table 6-8 Scenario analysis summary- Linear deterioration pattern

Linear Deterioration Pattern										
IMF (Years)	**FMF (Years)**	**IEE (GJ)**	**OE (GJ)**	**REE (GJ)**	**EOLE (GJ)**	**Total Energy (GJ)**	**OE savings (GJ)**	**Additional REE (GJ)**	**Net Savings (GJ)**	**Net Savings in %**
0	0	524,451	1,672,618	15,676	(36,712)	2,176,034				
20	16	524,451	1,651,306	23,906	(36,712)	2,162,952	21,313	8,230	13,083	6.1%
18	14	524,451	1,658,985	18,368	(36,712)	2,165,092	13,633	2,692	10,942	5.1%
15	11	524,451	1,645,278	23,551	(36,712)	2,156,568	27,340	7,875	19,466	9.0%
13	9	524,451	1,642,401	22,711	(36,712)	2,152,852	30,217	7,035	23,183	10.7%
10	4	524,451	1,635,783	27,319	(36,712)	2,150,842	36,835	11,642	25,193	11.7%

Note: IMF = Initial Maintenance Frequency; FMF= Final Maintenance Frequency.

For calculating the *"Net Savings"*, the share of operating energy pertaining to the best and worst performance of the external wall assembly is found out and the comparisons are made based on that value. It is assumed that the building will exhibit the best performance when the R-value of all materials in the material assembly is at its 100% performance level (as shown in Table 6-4). A test case simulation is performed in EnergyPlus wherein the R-value of all the materials under analysis (wall components and the windows) is changed to 40% of the initial value. OE obtained for both cases indicate that when the R-value of all the materials is at a 40% level then there is a 12.9% increase in the operating energy. Since the performance of the materials considered in this study is assumed between 100% and 40%, the savings obtained are also compared with this share of operating energy (i.e., 12.9% of cumulative operating energy).

For each deterioration pattern, all scenarios resulted in energy savings with respect to the base case. Interestingly, out of the analyzed maintenance frequencies, the best savings obtained for each deterioration patterns were not for the same maintenance frequency scenario. The best savings scenarios for linear pattern are with an initial maintenance frequency of 10 years, exponential pattern with 13 years and polynomial pattern with 15 years. To further verify the significance of these savings, t-tests are conducted on the monthly operating energy values of best-case scenarios and base case.

6.6.6 Statistical T-Tests

For this study, a paired two-sample test with a 95% confidence level is conducted to compare the energy performance of the base scenario (with no maintenance) and the best-case scenario obtained across each deterioration pattern. The data points considered are the OE values for the life cycle period of the building for 50 years. Paired test methodology is adopted because the individual data points (OE consumption for a year) across two data sets cannot be considered as independent since both scenarios are representing the same building, and essentially studying the effect of an intervention (material maintenance) on a base case. The primary aim of this T-test is to find out the significance of difference between the OE consumption between the base case and the maintenance case scenarios and the null hypothesis assumes that the difference of mean across both scenarios is zero, which hypothesizes that the savings obtained from the best-case scenarios are not significant from the base case. The t-test results obtained for each scenario are given below in Table 6-9. The results obtained indicate that in each of the deterioration patterns, the p-values are considerably smaller. This gives enough evidence to reject the null hypothesis, $\mu_1 - \mu_2 = 0$. This reiterates the fact that continuous maintenance on the building material assemblies can result in significant savings in the OE consumption in a building during the use and maintenance phase.

Table 6-9 T-Test results

Item	Exponential		Polynomial		Linear	
	Base Case (No Maintenance)	*Initial Maintenance Freq-13 years*	*Base Case (No Maintenance)*	*Initial Maintenance Freq-15 years*	*Base Case (No Maintenance)*	*Initial Maintenance Freq-10 years*
Mean	μ_1= 33,724	μ_2= 32,908	μ_1= 32,340	μ_2= 32,119	μ_1= 33,331	μ_2= 32,592
Variance	σ_1^2 =1,384,302	σ_2^2=401,194	σ_1^2 =1,111,570	σ_2^2=576,199	σ_1^2 =1,286,875	σ_2^2=377,392
Observations	50	50	50	50	50	50
Null Hypothesis (μ_1- μ_2)	0		0		0	
Degrees of freedom	49.0		49.0		49.0	
t-Stat	8.0		4.1		7.1	
P(T<=t) one-tail	1.1E-10		7.5E-05		2.1E-09	
t-Critical one-tail	1.67		1.67		1.67	
Decision	Reject the null hypothesis		Reject the null hypothesis		Reject the null hypothesis	

Furthermore, to understand the significance of the type of material deterioration on the total life cycle energy requirement, for each deterioration pattern, an average of total life cycle energy requirements is calculated from all scenarios and is shown in Figure 6-8 below. In comparison with exponential and linear deterioration patterns, the material assembly with a polynomial deterioration pattern results in lesser life cycle energy demands for this building case study.

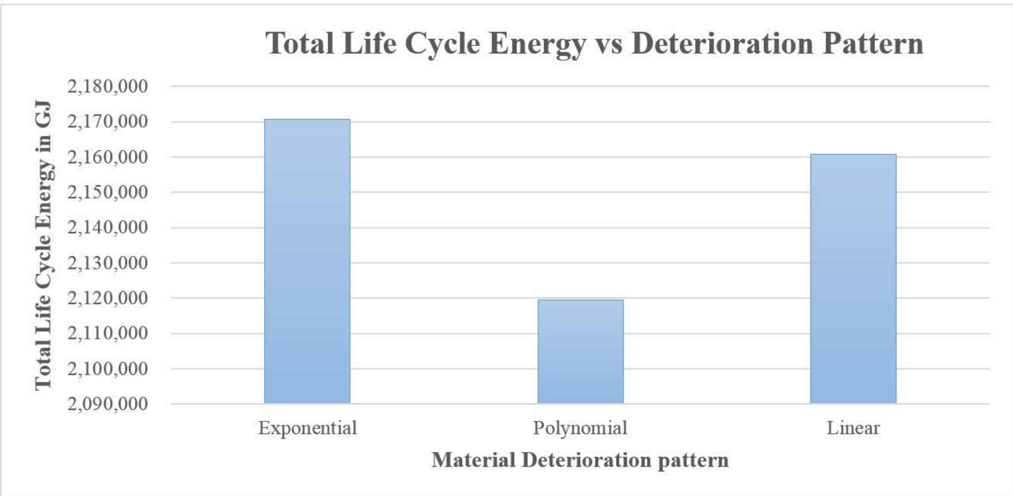

Figure 6-8 Total lifecycle energy across various material deterioration patterns

6.7 Discussion of the results

The significant finding from this study that can influence the building material selection process is that, materials following a polynomial deterioration pattern results in reducing the overall life cycle energy requirements compared to exponential and linear patterns. This is a very critical observation because the current focus of current material selection process is heavily dependent on material cost, appearance, durability and other sustainability aspects, but not based on the pattern in which the material deteriorates. Even though various studies concentrated on material service life prediction methods and others estimating the effect of varied material service life scenarios on embodied energy requirement, there has been very little focus towards measuring the actual deterioration pattern of building materials mainly because of the complexity in measuring the actual performance of a material during the use and maintenance phase. The findings from this study can be a strong motivation to pursue further research in this direction.

Another major observation is about the net savings obtained across all three deterioration patterns. With materials following exponential and linear deterioration pattern (where the performance of the material deteriorates faster initially unlike polynomial pattern), the effect of regular maintenance is evident in terms of the net savings obtained. A material exposed to marine environment can undergo faster deterioration due to the influence of multiple agents. The results obtained from this study indicate that regular maintenance in such cases can result in bigger savings. In addition, regular maintenance can help in keeping the material properties under control that extends the service life of the material. Performing several such scenarios can provide an optimum maintenance frequency to be adopted for a building that results in utilizing the maximum available service life from individual materials thus resulting in reduced life cycle energy requirements for a building.

Regular material maintenance also has other tangible benefits such as better occupant comfort, improved external appearance thereby sustaining the market value of the property, and maintaining weather tightness thereby providing better protection for various electrical and mechanical appliances inside the building. Often, maintenance or replacement is done when there is a noticeable failure or loss of function for any building material or assembly. In that case, the material might have already crossed the useful service life and this would have already affected the operating energy usage adversely. The framework proposed through this research can be a useful tool primarily for building facility managers who are faced with questions about the right time to conduct a maintenance or replacement of building materials.

6.8 Conclusions- Phase II

In this study, a SD model is developed that generates the impact of building material deterioration, maintenance and its corresponding impacts on the energy consumption. Anylogic 7.0.0 is used for creating the system dynamics framework and EnergyPlus is used for performing the energy simulations that interact with the life cycle data repository. Various scenarios were performed on the model to understand the significance of different material deterioration patterns and maintenance frequencies. Best-case scenarios for each deterioration patterns were identified based on the net savings obtained. Statistical t-tests are conducted on these best-case scenarios to determine the significance of the obtained results. The results indicate that adopting an optimum material maintenance schedule can result reducing the total energy requirements in any building.

On the computing aspects, this study has some limitations. The operating energy is estimated based on general equations based on energy simulation. The authors are now bringing the inter-operability aspects into the existing model to allow real time information exchange between system dynamics simulation and the energy simulation software program. Furthermore, the only feedback loop analyzed in the model is the dynamic maintenance frequency and its effects on the operating energy requirements. This study can be strengthened by adding additional possible loops such as cost aspects and effort required for a maintenance activity, effect of various types of building (e.g., high performance building) and so on.

Similarly, this study considered only external wall assembly for the simulation analysis by assuming the performance of all other material assemblies' constant. The performance of all other materials in a building can affect the operating energy requirement and considering the effect of other materials also can result in more useful observations about the energy performance of a building. In addition, there are many other factors such as occupant's energy use behavior, effect of climate changes, and efficiency of equipment and systems in the building that can affect the energy use in a building. In the future, the authors will extend the scope of this research initiative by including the factors to finally result in a user-friendly building life cycle energy analysis tool.

CHAPTER 7

Life Cycle Based Energy Monitoring Simulator

7.1 Summary

This study integrates the life cycle based building performance simulator developed in Chapter-6 with the occupant behavior simulator developed in Chapter-5, to develop an integrated life cycle based energy monitoring mechanism. This framework has the capability to represent the combined effects of several factors affecting the building's energy consumption (e.g., varying building performance and the occupant's dynamic energy use behavior), over a longer period of the building's life cycle. A framework like this can be beneficial to the various building practitioners to analyze the energy impacts of several factors in unison, and hence device better strategies for building operation. This study can also be found in Thomas et al. 2017b.

7.2 Background and motivation

As described earlier in Chapter-2, the current energy estimation approaches are spaced in two domains. Those are the life cycle based frameworks that adopted a cumulative based approach, and the co-simulation frameworks that incorporate the effects of various dynamic factors in traditionally static building energy simulation. The major limitations of the former include assumptions made about various building life cycle events (e.g., static material performance, fixed material replacement rates) to estimate the total energy requirements, and not considering the inter dependency between various energy requirements into full consideration. Meanwhile for the latter approach, the focus is only for a short-term period, i.e., maximum a year and therefore lack the capability to represent the effects of several energy influencing factors over the entire life cycle of a building. These limitations were individually overcome using the simulators developed through this dissertation. The building performance simulator developed in Chapter-6 has demonstrated how varying building operative conditions influence the life cycle energy consumption. This study adopted a life cycle approach and has the capability to represent the effects of several life cycle events on energy use. Meanwhile, the occupant behavior simulator developed in Chapter-5 proposed a new flexible framework to analyze the effects of occupant's dynamic energy use behavior. Both these studies essentially highlighted the importance of analyzing the energy effects of these two factors in a building's operation.

In addition to individually analyzing these factors or similar other factors, it is also equally important to understand the inter-relationships between several energy influencing factors in the buildings. For instance, the way in which the occupants operate the various systems in an old building need not be the same when compared to a newer building with highly efficient HVAC systems and materials with high thermal performance. Additionally, building retrofits, material maintenance and replacements occur during a building life cycle which also might affect the occupant's energy use behavior, over time. This is an inevitable research requirement, given the fact that around 30% of the energy in the commercial sector is going as waste due to inefficient and unnecessary use of building facilities (Energy Star 2015). To understand why this is happening, it is very important to have a mechanism that has the capability to perform life cycle based energy analysis in buildings by combining the effects of several factors. However, such a framework that performs a life cycle based building energy analysis by taking care of the effects of several factors, is still not visible in the literature. Therefore, an integrated energy simulation framework is necessary to delineate the effects of several factors that influence the energy consumption in the buildings, and understand why energy consumption sometimes goes up in the buildings.

Literature also supports the need for performing the energy analysis over a longer period. Through a Markov-chain based stochastic model, it was demonstrated that longitudinal variations of building conditions and weather conditions cause significant deviations from the predicted energy consumption levels (Wang and Shen 2012). Similarly, Wilde and Tian (2011) opinioned that the projected climate changes pause significant risks in the thermal performance of the buildings and hence the energy use. Likewise, Waddicor et al. (2016, 2015) predicted the 50-year energy consumption in a building, and found out that climate changes and ageing of buildings have a significant effect on the energy consumption. De Wilde and Coley (2012) similarly argued that the changing climatic conditions result in a shift in the energy use in buildings because of the decrease in heating and increase in cooling requirements. Likewise, Lindberg et al. 2008 found out that over the last three decades, the climate change had a significant impact on the energy use patterns in the buildings. Coincidently, Crawley (2008) predicted that the impact of climate change will result in an overall reduction of about 10% energy use in cold climates, and about 20% energy use increase in tropical climates, by the end of this century. Recently, Bros-Williamson et al. (2016) suggested that longitudinal analysis needs to be performed over longer periods of building operation to understand how building systems performance and occupant's energy use behavior influence the energy consumption.

All the above studies inform us the direction in which the future energy simulation domain should move. The next generation energy simulation tools should ideally simulate the energy requirements in a building for a longer period, considering the effects of events that occur during the life cycle. It is a widespread practice in the energy domain to have future energy projections about the energy use across different sectors, by considering assumptions about population growth, availability of fuel sources, rise/fall in demand and supply, to name a few (IEA 2016, DOE 2012). But in the building sector, there is a lack of a tool that has the capability to estimate the energy use at an individual building level as well as a bigger building stock, by considering the effects of several factors affecting the energy use. Such a tool would be an immense help to the various building stakeholders in designing energy efficiency strategies especially during the building maintenance and operation. Given the fact that, buildings use and maintenance phase accounts for 80% of its energy consumption (CSSBI 2013, UNEP 2007), creating such a framework is a necessity to understand the building science and its complexities occurring in a building's operation.

Therefore, the main aim of this study is to create a framework that run for the entire life cycle of the building simulating the individual events and its inter-relationships. This framework will have the capability to represent the real-time operation in a building, wherein people interact and choose decisions, building system failures occur that affect the building systems, and the equipment efficiency comes down drastically over time. All these actions have definite impacts on the life cycle energy use in the building. Hence the theme proposed in this chapter is by considering the effects of several such effects along the life cycle of the building. Figure 7-1 below denotes some of the events that happen along the life cycle of a building which are part of the proposed framework.

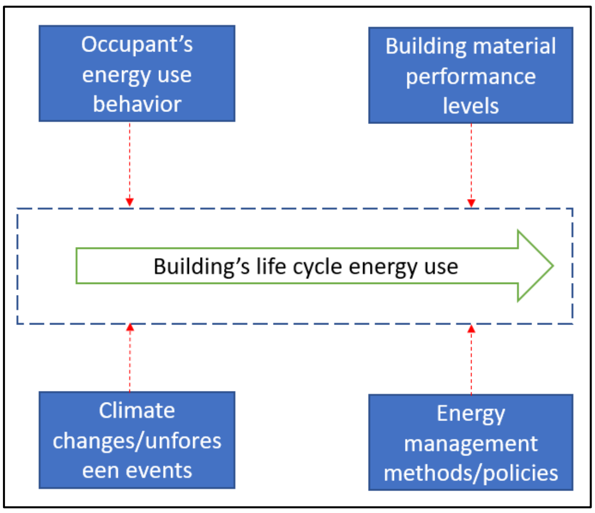

Figure 7-1 Factors affecting the energy use of a building in its life cycle

The two main objectives of this study can be therefore summarized as given below.

1. Develop a composable simulation framework that has the capability to integrate and analyze the combined effects of several factors affecting the life cycle energy use.
2. Demonstrate the usability of this framework by performing a case study involving building performance variation and the occupant's energy use behavior.

7.3 Methodology: Creating a distributed framework for composable simulation

The overall idea explained above demands several simulators connected to a life cycle based framework. To achieve these objectives, a four-phase methodology is adopted and is given in Figure 7-2 below. Overall, the methodology outlined below will demonstrate how multiple simulators can be connected to the energy simulation program to understand the combined effects of several factors in building energy use.

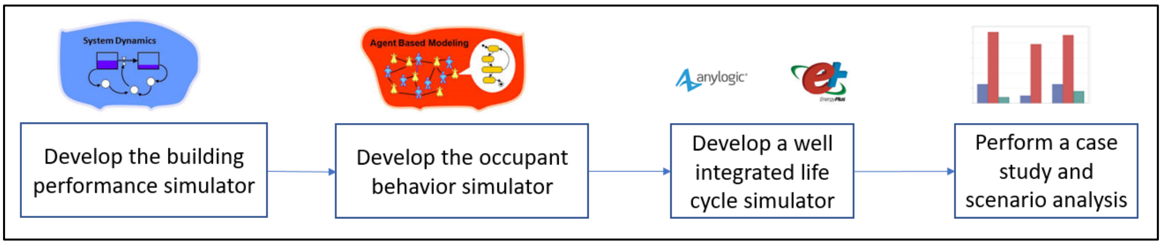

Figure 7-2 Methodology adopted for developing the life cycle based energy simulator

7.3.1 Phase-1: Developing the building performance simulator

A building performance simulator (BPS) is developed through this phase, by using the capabilities of the system dynamics model developed in Chapter-6. As a recap, this SD model simulated the effects of dynamic material performance and varying maintenance scenarios on the life cycle energy performance of the building. A typical simulation run is started by initializing the analysis period (e.g., 50 years), material degradation pattern (e.g., exponential pattern), and a maintenance period to be adopted (e.g., at every 10 years) to perform maintenance on the building materials. The main component in this SD model is the feedback loop that represents the effects of dynamic building performance variation on the operating energy consumption. In addition, one major assumption in this model was about the operating energy estimation using best-fit equations. Through this phase, the operating energy estimation procedure is modified by coupling this model with the energy simulator (e.g., and energy simulation program such as EnergyPlus), which allows us to calculate the operating energy based on the actual performance levels of various building materials (e.g., R-value of the thermal insulation).

This connection is made possible by adding additional programming scripts that exchange the modified building model input file to the energy simulator (ES). A conceptual execution sequence for achieving this connection is described through the Figure 7-3 below. At every time step of the BPS, a modified model with the actual performance levels of several materials (e.g., actual R-Value) in the building is generated. This is made possible by editing the building energy model file. In EnergyPlus, the input model file has a text file based format (*.idf*), which is easily editable from a programming interface. In this case, the editing and the saving as a building model file is made possible from the SD interface using java codes. Figure 7-4 below demonstrates a snippet from the script used for achieving this feature. Once such a model is generated, the BPS pauses temporarily till the ES estimates the energy use (for the current building performance level) by co-simulating with the other simulators (As demonstrated through Figure 7-3).

The simulators connected to the ES represents various dynamic behavioral components affecting the energy use in the building (e.g., occupant behavior, climate change). The development of one such simulator is explained in Phase-2 of the methodology below. Once the ES finishes the co-simulation with the other simulators, the actual operating energy information is conveyed to the BPS and this trigger the BPS to restart. In short, the operating energy information, which was earlier calculated by means of best-fit equations, is now estimated by means of connecting with the energy simulator. This coupled simulation process continues for the desired building cycle period as initialized by the user (e.g., 10 years, 50 years).

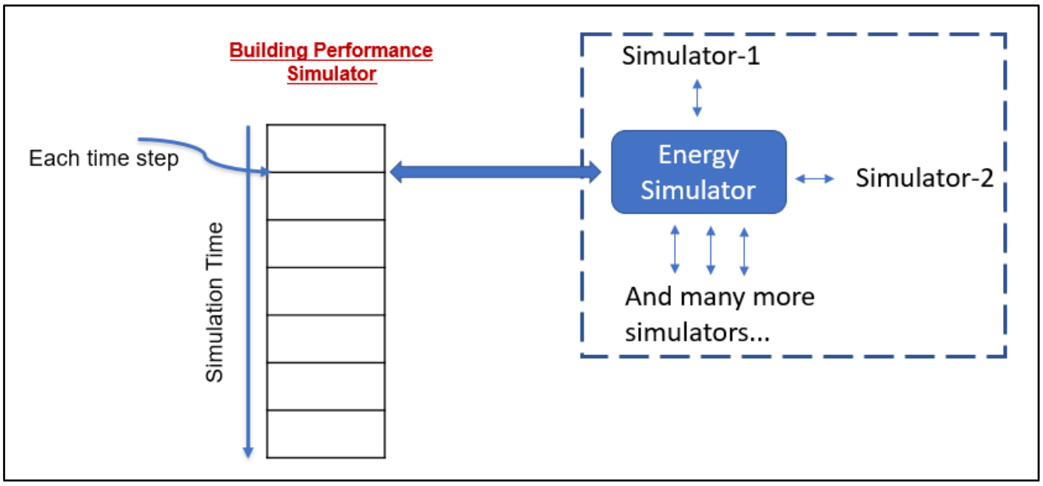

Figure 7-3 Connection mechanism of BPS with other simulators

```
array[1]="!Edited EnergyPlus File"; // A statement at the start of the file
try
{
    int k=1;
    FileWriter fw = new FileWriter("C:\\Users\\albertth1\\Desktop\\Modified.idf");

    for (k=1;k<i;k++)
     {
        fw.write(array[k] + "\n");// Wiritng to the new idf file
     }
     fw.close();

 }
   catch(IOException ie)
   {
        ie.printStackTrace();
   }
```

Figure 7-4 Code snippet showing saving a new building energy model file

7.3.2 Phase-2: Developing the occupant behavior model simulator

Through this phase, the methodology to connect a simulator to the BPS and the ES is demonstrated. The main idea behind this connection is to integrate the energy effects of a new factor (e.g., occupant behavior, climate change) in addition to the building performance. In this study, this is demonstrated by modifying the occupant behavior simulator (OBS) developed in Chapter-5 by establishing the necessary connections to the framework.

The occupant behavior model developed in Chapter-5 analyzed the dynamic effects of clothing adjustment behavior and the thermostat set point behavior in the buildings. Through this phase, the capabilities of this model are enhanced by providing more behavioral opportunities. Occupants typically adopt several behavioral options to achieve comfort, while living and working in buildings. In a winter climate, the typical behavioral choices are adjusting the clothing levels, adjusting the thermostat set points, and turning a personnel heater ON/OFF (Zhao et al. 2015, Hong et al. 2015b, Langevin et al. 2015). Similarly, in the summer, the behavioral choices include adjusting the clothing levels, adjusting thermostat set points, turning the personnel fans ON/OFF, and opening/closing windows (Zhao et al. 2015, Hong et al. 2015b, Langevin et al. 2015). As discussed in Chapter-2, the default energy simulation programs do not represent the dynamism involved in these behavioral patterns, but assume fixed schedules and parameters for representing the variations in these behavioral options (e.g., thermostat set point set at a constant level for the entire day). The sections below explain the methodology through which this enhancement is achieved.

7.3.2.1 Enhancing the occupant behavior model by representing more behavioral opportunities

In addition to the features provided by the model in Chapter-5, two more behavioral adaptations are added in the occupant behavior model. In the winter period, occupants can now modify their clothing levels, adjust the thermostat set points, and can use a personnel heater to gain thermal comfort. Similarly, in the summer, they can adjust the clothing level, adjust thermostat set point and can use a personnel fan. In this study, buildings are assumed to be fully climate controlled and therefore, the window opening/closing behavior is currently not incorporated into the model, and is being considered as a future part of this study.

Figure 7-5 and Figure 7-6 below show the algorithms adopted for representing the behavioral adaptations in winter as well as in the summer. The concept is similar to the method employed in Chapter-5. On a continuous basis, occupants vary their clothing levels based on the peer pressure and interventions that occur in the building, and at every time step (e.g., an hour), occupant's PMV levels are estimated based on the building ambient conditions, clothing and the activity levels. Based on the individual PMV levels of the occupants, a zone level PMV level is then estimated. If this PMV level is not in the comfortable range, then suitable behavior choices are selected by the occupants for that zone. In winter, if occupants are feeling cold, they will either increase the thermostat set point based on the mean vote or will decide to use personnel heaters under their desks. If they are feeling hot, then the thermostat set points are reduced. Similarly, for the summer period, the choice is between using a personnel fan or a thermostat. In both the seasons, If the occupants are feeling comfortable (PMV range is between -0.5 to 0.5), then no action is assumed in the building, which is typically the case.

$PMV_{(i,\,j)}$	(comfort level of the occupant *j* in zone *i*)
$PMV_{(i)}$	(Estimating the zone PMV level)
$V_{(i)}$	(Estimating the zone level occupant vote)
If ($PMV_{(i)}$ > 0.5)	(Occupants feeling hot)
$t_{(i)} = t_{(i)} + v_{(i)}$	(Adjusting the set point based on vote)
Else if (PMV (i) < 0.5)	(Occupants feeling cold)
$t_{(i)} = t_{(i)} + v_{(i)}$	(Adjusting the set point based on vote)
OR	
Switching ON the heater	
Else	
NO ACTION	(Occupants comfortable)

Figure 7-5 Occupant behavior choice algorithm- Winter season

$PMV_{(i,j)}$	(comfort level of the occupant *j* in zone *i*)
$PMV_{(i)}$	(Estimating the zone PMV level)
$V_{(i)}$	(Estimating the zone level occupant vote)
If ($PMV_{(i)} < 0.5$)	(Occupants feeling cold)
$t_{(i)} = t_{(i)} + v_{(i)}$	(Adjusting the set point based on vote)
Else if (PMV (i) < 0.5)	(Occupants feeling hot)
$t_{(i)} = t_{(i)} + v_{(i)}$	(Adjusting the set point based on vote)
OR	
Switching ON the fan	
Else	
NO ACTION	(Occupants comfortable)

Figure 7-6 Occupant behavior choice algorithm- Summer season

Every such decision taken by the occupants in a zone has an impact on the energy simulation program. Therefore, at each time step of the OBM, the occupant behavioral choices (e.g., zone-1 opting for reducing thermostat set point by *'1'* degree Celsius, Zone-4 opting for switching on a heater) are then conveyed back to the energy simulation program by using the capabilities of the LABS framework. These feedbacks and its representation in the energy simulator are mentioned in the below sections in detail.

Representing the variations of thermostat set point in EnergyPlus is quite straightforward and was demonstrated in Chapter-5 by modifying the heating and cooling schedules. However, representing the behavioral opportunities such as the heater ON/OFF and fan ON/OFF are not quite straightforward, because those are not direct schedules in the energy simulation model. Studies have adopted indirect methods to effectively represent these behavioral choices. For instance, Langevin et al. (2015) represented switching on the heater in a zone by increasing the local zone wise air temperature and radiant temperature, and by increasing the zone wise internal equipment gain. For turning on the fans also a similar procedure was adopted, i.e., by increasing the zone wise equipment internal gain, and by increasing the local air velocity. Typically, these behavioral patterns are predicted by the occupant behavior model, and these patterns will have a feedback to the energy simulation model. For instance, if the occupants' preference is for switching on the heater in a zone, the feedback to the corresponding energy model would be increasing the zone level equipment gain by a definite power level. Langevin et al. (2015) adopted 600 W to 1200 W of equipment gain increase for a typical heater ON behavior. Similarly, for switching ON a fan, electrical equipment gain is increased by 15W. Table 7-1 below summarizes the occupant decisions and the corresponding feedback to the energy simulation model. The zone wise impacts in the EnergyPlus side is adapted from Langevin et al. 2015, that performed an onsite measurement of various heater and fan options to measure the typical impacts in a closed building environment.

Table 7-1 Message exchange between OBS and ES

At OBS	Impact in OBS (Local level)	Feedback to ES
Clothing level adjustment	Changing the clothing levels of occupants	Revised zone wise clothing schedule
Thermostat set point adjustment	No local impacts, but will result in changing the ambient conditions	Revised zone wise heating/cooling schedule
Heater ON	+2 Degree Celsius increase in local air temperature/radiant temperature	Conveying the addition to the zone level equipment gain (+ 800 W)
Fan ON	Increase in local air velocity by 0.75 m/s	Conveying the addition to the zone level equipment gain (+15 W)

In addition, one more modification is done in the OBS. Typically when compared to the winter clothing level, occupants have a lesser clothing level during the summer time. Therefore, the clothing level for summer months is modified to be between 0.3 Clo to 0.6 Clo. Earlier, the range was between 0.3Clo to 1.3Clo. Literature also supports selecting such a clothing range. Zhao et al. 2014 has considered a summer clothing level of 0.7, and the default summer clothing level considered in EnergyPlus is 0.5 Clo, and therefore a clothing level between 0.3 Clo to 0.6 Clo is assumed reasonable. In summary, the occupant behavior model developed in Chapter-5 has been modified to provide more behavioral options. This OBS now has the capability to perform a co-simulation with the ES and an analysis like this would provide options for understanding how people behave and how much those behavioral patterns can influence the energy use in the building.

7.3.3 Phase-3: Developing the integrated building life cycle energy simulation framework

Through this phase, the BPS, ES and the OBS are coupled together to create the life cycle based energy simulation framework, that analyzes the combined energy effects of several factors. Figure 7-7 below shows the time synchronization diagram for realizing this coupled framework, and the flow of data across these three simulation modules are given in Table 7-2 below.

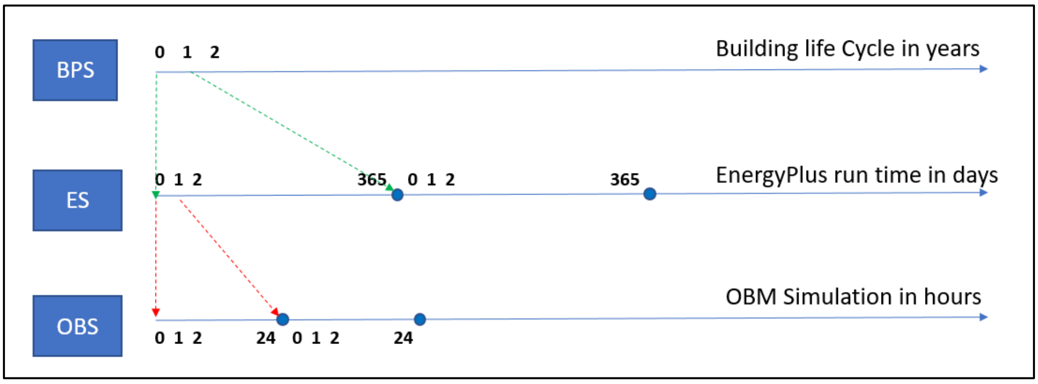

Figure 7-7 Time synchronization diagram

A one-year time step is considered for the BPS. This time step is assumed to be reasonable because a building's entire life cycle is being analyzed. For instance, if a 50-year life time is assumed for a building, then the BPS would generate building models for each year of its operation, i.e., 50 models in total. Each such model embodies the performance level of the building at the end of that specific year. This model is assumed to represent the material performance levels of the building for that specific year.

Table 7-2 Data exchange mechanism

Steps	Description
1	The BPS starts a typical building performance simulation by taking inputs about the building. The input to BPS is a building model.
2	At time step-1, the BPS outputs a modified building model with building performance parameters (modified R-value of insulation materials), and it temporarily pauses the simulation.
3	This trigger starting the ES automatically, by taking this modified building model as the input model.
4	The OBS is started manually for the first time. This manual start is necessary because the Anylogic version used for this study is the university researcher option, which does not provide options for starting an Anylogic model automatically.
5	ES and OBS performs the coupled simulation for the first-year period.
6	ES stops after one year and generates the outputs.
7	OBS pause temporarily after a year period.
8	BPS restarts and gathers the actual energy use information.
9	BPS generates the model representing the next year.
10	Steps 1-9 repeats.

Once the modified energy model is generated by the BPS, the ES is automatically started for that year thereby initiating a co-simulation with the OBS. This means that the ES is performing the energy simulation by incorporating the building performance (through the modified building performance parameters), and the occupant's energy use behavior (through the real-time feedback received from the OBS). While this co-simulation occurs, the BPS would be in a paused state waiting for the energy consumption information. A one hour time step is adopted for the co-simulation between ES and the OBS. At each time step, the OBS receives the building ambient condition parameters from ES and exchange the occupant behavior patterns (e.g., new thermostat set points, turning heater/fan ON) back to the ES. Once this co-simulation reach the time step of the BPS, (i.e., one year), the ES exchanges the energy consumption information back to the BPS, which will allow the BPS to restart from the earlier paused state. This entire coupling process repeats for the desired life cycle period in the building automatically. Otherwise stated, once initiated, this framework runs for the entire life cycle of the building by simulating the life cycle energy requirements incorporating the effects various dynamic factors.

An analysis and time synchronization mechanism like this ensure that building performance and the occupant's behavior is integrated into the energy analysis. This is very critical because the occupant's behavioral patterns need to be analyzed in the backdrop of varying building performance levels. Similar to this procedure, more simulators (e.g., climate change simulator) can be easily incorporated to this framework in the future. In the next phase, a case study is performed to demonstrate the capabilities of this framework.

7.3.4 Phase-4: Case study and performing scenario analysis

A building model located in Chicago is selected for demonstrating the capabilities of the framework. This model is the same case study model used in Chapter-5. As a recap, this building is a single storied, five zone office building (one core and four perimeter zones) with a total floor space of 511 m2, a window to wall ratio of 21.2%, and 10 occupants in each zone. The analysis period considered is 50 years. In the BPS side, the material assembly selected for the analysis is the external envelope consisting of wall materials and the windows, and the material property selected for the analysis is the R-value of the materials. The materials in this assembly are assumed to be deteriorating in an exponential pattern and a maintenance is assumed to be performed at every 5 years. Once the BPS is initialized like this, a typical integrated simulation run can be started. At every year of the simulation, BPS generates building model file with updated R-value of the materials, and a co-simulation will be performed by the ES with the OBS using this updated building model. Through this mechanism, this framework integrates the effects of deteriorating material's R-values and the occupant's energy use behavior. This coupled simulation will end at 50 years.

The assumptions in the OBS side are same as the Scenario-3 considered in Chapter-5. Each occupant is assumed to be connected to eight other occupants and the peer pressure between the occupants results in occupants modifying their clothing levels. In addition, an energy intervention is planned at every 3 hours in the building which will also influence occupants to change their clothing levels. As the day progresses, based on the varying PMV levels of occupants, they adopt several behavioral choices. A one hour time step is adopted to exchange the zone level behavioral adaptation information to ES.

Figure 7-8 below shows the results obtained from performing a coupled simulation for a 10-year analysis period. Three lines are plotted in this figure. Each data point in each of these lines represents the annual energy consumption measured for a specific year. The blue line is the base case. It shows the annual energy consumption value (estimated by performing an EnergyPlus energy simulation on the case study building model), and is assumed to be constant over the analysis period. This assumption is made because the current energy simulation schemes only offer the capability to perform an annual energy simulation. The orange line shows the energy consumption patterns when only the building material's performance variation patterns are considered, i.e., when the occupant's energy use behavior is not incorporated into the analysis. This is analogous to the results generated in Chapter-6 of this dissertation. It can be seen from the figure that he energy consumption is increasing steadily when material performance degrades, and at 5th year and 10th year, there is a reduction in the energy consumption, because of the performed maintenance in the building Meanwhile, the green line shows the energy consumption when the varying building's performance as well as the dynamic occupant behavior is analyzed in unison. The first observation from this line is that when occupant's energy use behavioral choices are also incorporated, the energy consumption to going up compared to the orange line. The reasons for these rise in energy consumption, and the effects of varying building performance on the occupant's energy use behavior is further investigated below.

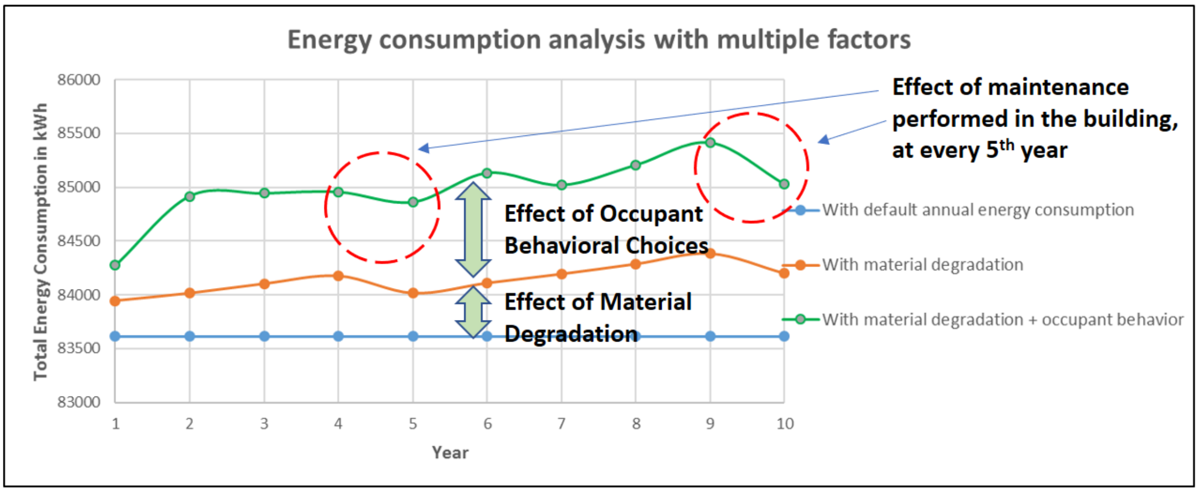

Figure 7-8 Effects of multiple factors on energy consumption

Figure 7-9 shows the mean annual thermostat set points for the winter and the summer seasons for the entire analysis period of 10 years. For the winter season, the mean thermostat set points desired by the occupants is above the default winter set point level of 21 degree Celsius. Similarly, the set points desired in the summer season is below the default level of 24 degree Celsius. This is the major reason for the energy use to go up in the building. Other reason is occupant's use of heaters and fans, which increases the electricity use in the building.

One interesting point here is, even though there are sporadic up and down in the winter set point levels, there has been a general trend of increase in the thermostat set point over the years as shown by the red arrow. From year-4 to year-5, there has been a slight decrease (the maintenance performed will have an effect for this decrease), and since then, when the building's performance comes down, thermostat set points desired by the occupants generally rise. This is one critical observation from this study. Again, a maintenance performed at 10th

year is having an effect on reducing the thermostat set point requirements. This is a clear indication on how building performance influence occupant's behavioral choices. The summer thermostat set points however doesn't show much effects over the analysis period.

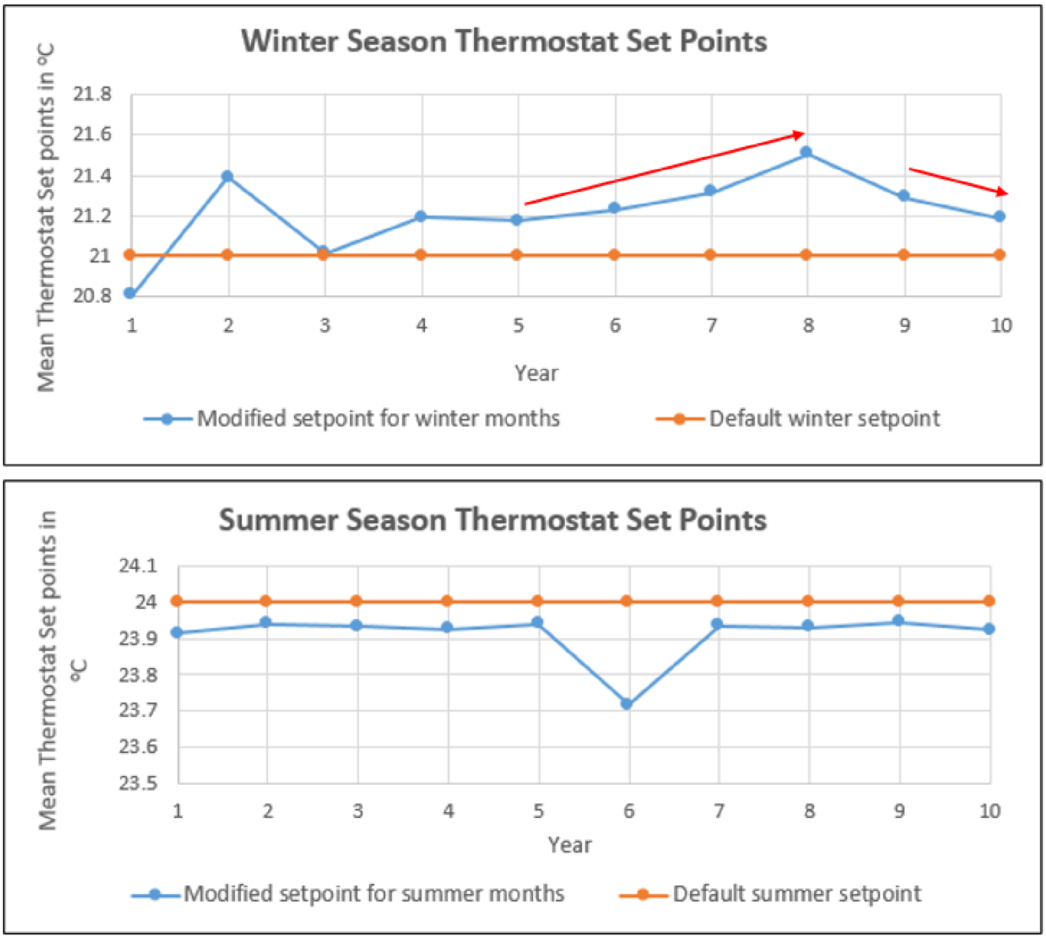

Figure 7-9 Winter and summer thermostat set points

In addition to the thermostat set point analysis, in Figure 7-10 below, how occupant's behavioral choices vary over the analysis period is demonstrated. Otherwise stated, Figure 7-10 informs the share of a behavioral option in the building for a year (e.g., In the second year, 5% of the time occupants choose to switch on the heater in the building). In this way, Figure 7-10 (a) plots the year wise share of the heater use for the entire 10-year analysis period. Similarly, Figure 7-10 (b) plots the share of fan use, and Figure 7-10 (c) plots the share of thermostat set point adjustments. Meanwhile, Figure 7-10 (d) plots the percent of time occupants does not choose any actions, or in other words the % of time occupants are comfortable in the building's current state of ambient condition. One thing to note here is that, the clothing behavioral choice is adopted by the occupants on a continuous basis in the building and therefore not counted for determining this share.

Even though, there is frequent up and down in these graphs as well, one common observation that can be made is that, during the maintenance years, i.e., at 5th and 10th year, there has been a decline in the adoption of all three behavioral choices (Barring the thermostat set point changes in the 10th year which shows a slight increase), and a corresponding increase in the no-action choice. These observations are highlighted by the red arrow in the figure. This is a direct indication that when a building's performance increased by a maintenance activity, it influences the occupant's behavioral choices. In other words, if the building is in good performing condition, then that will have an impact on occupant's energy related actions. An observation like this could be drawn only because of the combined analysis of the effects two factors in the building, and therefore highlights the importance of performing more such analyses in the energy simulation domain.

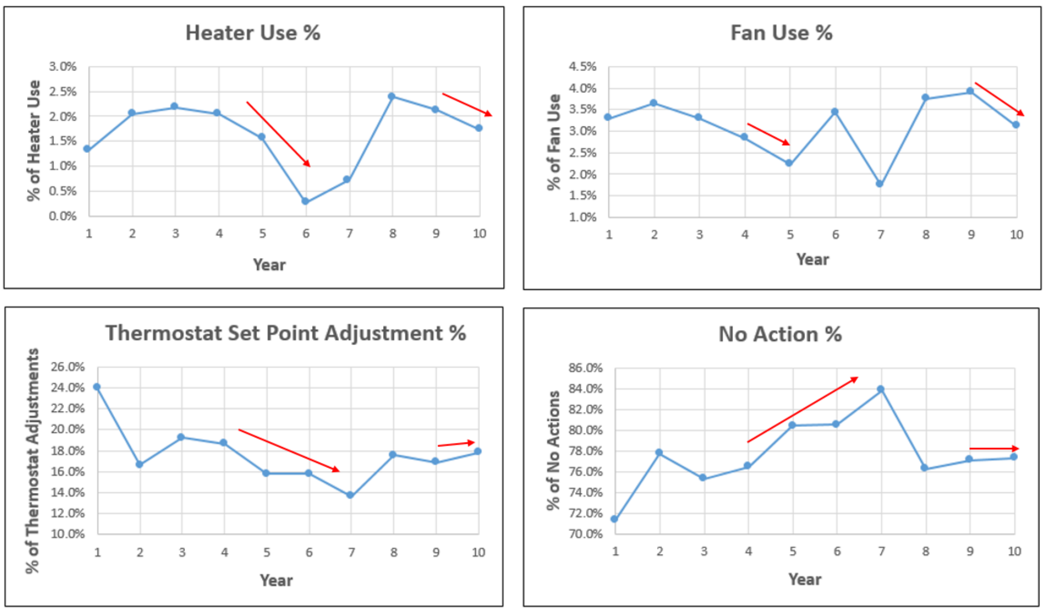

Figure 7-10 Share of behavioral choices across the analysis period

7.4 Discussion of the results

The results obtained through this study showed the importance of analyzing the building's energy consumption and the influencing factors over a longer time frame. Performing an analysis like this would provide options for understanding why the actual energy consumption is going way off from the predicted energy consumption levels. The current co-simulation frameworks offer capabilities to perform such an analysis only for a year period. But, this study demonstrated how such an analysis can be performed over a longer period of building life cycle. Several simulators as suggested through this study can be modeled separately, and the flexibility of LABS framework would allow a modeler to connect it to this life cycle energy monitoring framework to analyze the combined effects.

7.5 Conclusions– Phase III

There are several limitations in this study. The case study only analyzed the effects of only two factors, i.e., the performance of external envelope consisting of walls and windows and the occupant's energy related behavior. But there are several factors that affect the energy use in a building, over a longer period such as the efficiency of building mechanical systems, effects of varying climatic conditions, to name a few. However, given the flexibility of the LABS framework, this can be easily incorporated into this framework by adding more simulators into the loop. The main purpose of this chapter was to create a basic framework, and perform a case study to demonstrate how several factors interact and affect the energy use in a building, over a longer period in a building's life cycle.

The future energy simulations should be moving in this direction. That means, it should be able to incorporate the effects of various dynamic factors occurring during the life cycle of the building. The current approach only has the capability to perform an annual simulation approximating the diversities through static schedules and input parameters and therefore does not represent the true building behavior. Only a futuristic energy simulation framework like the one developed through this chapter can help understand the dynamism occurring in a building's entire life cycle.

CHAPTER 8

Verification and Validation Approaches

8.1 Summary

Verification and validation is a crucial step in any simulation based analysis as it determines the accuracy of the models, and its readiness to use for real-time purposes. Through the previous chapters, simulation models were developed to analyze the energy effects of varying building performance and occupant's energy use behavior. The verification and validation measures adopted for these models were individually discussed in the respective chapters. However, through this chapter, the general verification and validation methods adopted in the simulation domain are discussed, and the methods that are chosen for this dissertation are summarized.

8.2 Major validation and verification measures

A model is a substitute to a real system, and is used for learning the general behavioral trends of the system (Sargent 2013, 2000). Since only the major features are represented in a model, it is very important to make sure that the developed models represent at least the main aspects of the real system. Simulation based studies use appropriate verification and validation techniques to determine the accuracy of the developed models.

Verification methods involve detailed assessment of the model functionalities (Petty 2009, Sargent 2000). The purpose of this phase is to verify that the model is running and delivering the intended purpose. Verification process ensures that mistakes has not been made in implementing the model. Meanwhile, validation of the model involves checking the main assumptions to find out whether the accuracy of the model is consistent with its intended purpose (Sargent 2013, Petty 2009). In general, verification involves in identifying and removing the errors, and validation is concerned with quantifying the accuracy of the model (Thacker et al. 2004). Table 8-1 below summarizes some of the most common verification and validation techniques adopted in simulation based studies.

Table 8-1 Common verification and validation techniques (Adapted from Dutle et al. 2015, Sargent et al. 2013, 2000, Petty 2009, Roache 1998)

Verification Techniques	**Description**
Animation	The operational behavior of the model is checked through various visualization techniques. For instance, in a model that simulate the activities in a factory, the movement of components in the model are investigated for its correctness.
Structured walkthrough	The codes of the model are checked line by line for correctness and verifying whether it meets the intended purpose.
Trace	The behavior of a specific type of entity is traced through the model to determine whether the model logic is correct.
Validation Techniques	**Description**
Comparison to other models	In this method, the results from the model is compared against other valid models for the accuracy of the results.
Data relationship correctness	Data relationship correctness requires the data to have proper values regarding relationships that occur within a type of data.
Event validity	In this validation method, the events of occurrences in the model are compared against the actual events.
Extreme condition test	The model is checked against extreme inputs. For instance, if process inputs are zero, then the product output should be zero.
Face validity	Opinion is sought from individuals knowledgeable in the field about the behavior of the model to check whether the results are reasonable or not.
Historical data validation	If there is historical data available, part of this data is used to build the model and the other part is used for validating the model.
Internal validity	Several replications of a stochastic model are run to check the variations in the output. A large amount of variability means the model's results are questionable.
Multistage validation	This stage includes testing the validity of the model at several aspects. This method consists of developing the model on theory, observations, and general knowledge. Subsequently, the model assumptions are validated by empirically testing them and comparing the input output relationships of the model to the real systems.
Parameter variability and sensitivity analysis	This technique consists of changing the values of input and internal parameters of the model to determine the effect upon model's behavior or output. The parameters that cause significant changes to the output should be made accurate prior to using the model.
Predictive validation	In this technique, the model is used to predict the behavior of the system. The system's actual behavior is checked against the model's prediction to see whether both are the same.

8.3 Verification and validation measures adopted for this dissertation

Adopting a suitable verification and the validation technique is often a subjective decision based on the context in which the model is developed (Sargent 2013, Roache 1998). Often a combination of methods is used for verifying and validating the simulation model. Some of the methods discussed in Table 8-1 above are used for verification and validation of models developed in this dissertation. Even though the methods adopted were discussed in detail in the individual chapters, it is briefly summarized here again.

8.3.1 System dynamics based life cycle simulator

The major theme adopted in the life cycle based system dynamics simulator was representing the energy effects of dynamic building performance, over a building's entire life cycle. The ideal way to validate such a model is through a historical data validation method that explore the energy consumption patterns subjected to varying building material and system performance. However, one pre-requisite for adopting such a validation technique is the availability of enough data points on varying building performance and its energy effects. But, studies assessing the long-time material performance variation patterns are limited to only assessing the performance of few materials (e.g., external cladding materials) with no focus on representing its corresponding energy effects (Keisk et al. 2005, Gaspar et al. 2005, Sohet et al. 2002, and Harris 2001). Therefore, the major challenge faced in verifying and validating the SD framework is the lack of data points that inform how varying material and system performance influence the real-time energy consumption in the buildings.

Therefore, for verifying the SD model, first, the correctness of the codes in the model is verified using the structured walk through approach. Second, using the animation approach, the behavior of the model is ascertained for consistency. In this model, the main noticeable component is the system dynamics feedback (explained in section 6.4.2) that visualized the effects of maintenance performed on the operating energy flow. This aspect is checked by running several simulations to make sure that the feedback is working as intended during the model development stage.

Once the model is verified in such a fashion, a two-fold approach is adopted for validating the model. First, a historical data validation technique is used for validating the operating energy requirements generated for the case study building model. Existing operating energy information that is publicly available for the case study location (Chicago) is used for validating the accuracy of results produced by the SD model. It is mentioned in detail in Section 6.6.3 of this dissertation. Through this validation check, the operating energy requirement generated by the SD framework was found to be within 6.5% of the actual operating energy data for buildings of comparable size. Given the fact that the operating energy consists of around 80% of the total building's total energy, it is considered as a reasonably good approach of validating the results obtained through the model.

Furthermore, a parameter variability and sensitivity analysis is conducted for validating the technical and computing aspects along with verifying the model accuracy. Several real building maintenance scenarios are selected to test the sensitivity of the model across the three common material deterioration patterns (exponential, polynomial and linear). The results proved that the building performance widely varied across the tested deterioration patterns, and the varying material performance has an important effect on the total energy consumption. The significance of these results was also tested using a statistical T-test, and the T-test results informed that the energy savings suggested by the SD model are significant. This is also a clear indication that the performance of various building materials and the material maintenance scenarios influence the energy use considerably.

8.3.2 LABS framework and the coupled energy simulation

The LABS framework developed through Chapter-5 essentially showed how occupant's energy use behavior influences the energy consumption patterns in a building. For verifying the LABS framework, a structured walkthrough approach is adopted, and the correctness of the codes are ascertained. In addition, as explained through Figure 5-3 of Chapter-5, the message exchange sequence is designed in such a way that if there is a message drop across the connected simulation modules, then the framework itself stops working. It is an effective way of making sure the message exchange mechanism of the framework is happening as intended.

Furthermore, for validating the LABS framework, a parameter variability and sensitivity analysis is adopted. The energy effects of varying thermostat set point behavior of occupants were demonstrated using the LABS framework. A case study analysis was conducted with three scenarios with varied network connections and intervention mechanisms. This analysis informed us the effectiveness of the LABS framework in representing the dynamism in buildings. The results also showed that the occupant's thermostat set point behavior influences the energy consumption. This scenario analysis is mentioned in detail in section 5.4 of this dissertation. In addition, the occupant behavior model used for this study was a case study analysis of an already validated approach. Similarly, the energy model was developed in EnergyPlus which is also a thoroughly validated tool.

To verify the accuracy of results produced by the LABS framework, additional energy simulation analyses were conducted to see how much sensitive is the total energy use, to the changes to the thermostat set points. The results obtained are tabulated in Table 8-2 below. The first row shows the total energy consumption for the default case, i.e., with the default heating set point of 21^{o}C, during the building occupancy hours. Second and third rows show the energy savings possible when the thermostat set points are set at $\pm 1^oC$ away from the default 21^oC. One point to be noted here is that these results are gathered by fixing the thermostat at a constant level. To verify the accuracy of the results provided by LABS, the mean thermostat set point change occurred for the scenario-3 is estimated as -0.18 ^oC, and one more energy simulation is conducted by incorporating this set point change in the building model. This energy savings obtained for this case matches exactly with the savings produced by the LABS. Thus, the energy savings information shown in Table 8-2 when cross compared with the energy savings and the thermostat set point changes, also validate the capabilities of LABS framework in representing the dynamism within a building.

Table 8-2 Energy saving limits with respect to the base case

Simulation Run	Heating Set point	Total Energy in kWh	Energy Savings in %
1	21^oC	550.4	-
2	$21^oC - 1^oC$	510.7	7%
3	$21^oC + 1^oC$	594.5	-8%
4	$21^oC – 0.18^oC$	541.9	2%

8.4 Conclusions- Verification and validation

The models created in this dissertation are verified and validated using appropriate approaches suggested in the literature. One extended way of validating the SD framework is to apply several maintenance scenarios over the entire life cycle of a real building to see how the operating energy varies. But, one limitation of such an approach is that it is a very lengthy process and hence not considered to be a part of this study. Similarly, the LABS framework can also be validated by adopting a historical validation approach. For this, the main requirement is to measure the occupant's thermal comfort related behavior and actions over a longer time frame. The occupant's varying comfort levels and the behavioral patterns thus recorded can be used for validating the results obtained through the LABS framework. However, this step is considered as the next phase of the study and hence not included in this dissertation. Next chapter discusses the major conclusions and takeaways from this dissertation.

CHAPTER 9

Conclusions and Final Remarks

9.1 Summary of research methods

This dissertation mainly addressed the limitations of existing co-simulation frameworks in the building energy analysis domain, by developing a new distributed co-simulation framework, Lightweight Adaptive Building Simulation Framework (LABS). The LABS approach has helped to understand the energy effects of dynamic building performance and occupant's adaptive behavior on energy consumption. The main methods adopted for developing this framework are distributed co-simulation using Lightweight Communications and Marshalling, agent based modeling, system dynamics simulation and energy simulation. In general, the simulators developed through this dissertation have generally advanced the knowledge, by providing a systems-thinking approach and a new distributed co-simulation technique to analyze the various components of building science. The following sections provide a summary of how the research questions were addressed, and the future research directions that can be considered as an immediate follow up to this study.

9.2 Summary of research questions and contributions

Objective #1: To what extent can a lightweight communication mechanism be robust enough to support the development of the proposed distributed co-simulation scheme?

The LABS framework was developed using the capabilities of a lightweight communication approach, LCM. This study has effectively demonstrated that a lightweight approach can bring simplicity and usability from the perspective of a system designer. A modular scheme like this will allow program designers to model any complex system using different modules distributed across several work stations. Such a scheme will make modularity and error detection easier. Given the fact that LCM is supported by all the major computing platforms (Windows, Macintosh, and Linux), and building LCM in a computer is relatively straightforward, the ideas illustrated through this dissertation will find applications in domains other than building energy simulation.

Another feature of the LABS framework is the flexibility to incorporate a wide array of simulation programs into the co-simulation loop. In the existing frameworks, either the connection framework itself has a steep learning curve (e.g., BCVTB, HLA) or the rules do not allow incorporating disparate simulation programs. The introduction of LCM in LABS promotes distributed simulation, and shifts the connection sequence programing to the individual models. This means that each program controls when to send and receive data, and thereby facilitate a direct connection scheme across various simulation systems. This study also demonstrated how two programs run in parallel across distributed workstations while exchanging the relevant data. These features of LABS can help modelers and program designers in creating multiple simulation programs in distributed workstations to analyze the complexities occurring within a system quite effectively. Furthermore, this approach promotes the reuse of old models and programming scripts. This was demonstrated by remodeling an earlier published agent based model, to analyze the energy effects of occupant's thermal comfort related actions. The case study section of Chapter-5 exclusively dealt with this idea and by using the LABS framework it was demonstrated that by controlling the clothing levels of occupants, energy savings could be achieved in the buildings.

Therefore, through the LABS framework, it is demonstrated that a lightweight mechanism is robust enough to represent the dynamism that occurs in a building's lifecycle.

The LABS framework can represent the features currently provided by the existing schemes and in addition, can support distributed simulation.

Objective #2: To what extent can a systems approach be used to study the effect of dynamic building performance on buildings' life cycle energy requirements?

Chapter-6 has developed the SD framework that analyzed the effects of building performance on the energy consumption. The results obtained from this study indicated that incurring REE in an optimum way (for performing maintenance activities) can help bring down the OE consumption in the building, thereby also minimizing the total life cycle energy. In addition, regular maintenance can help in keeping the material properties under control that extends the service life of the material. Therefore, performing maintenance in a timely fashion is very critical to maintain the building performance under satisfactory limits. The framework developed through Chapter-6 can be used for performing several such scenarios to determine an optimum maintenance frequency in the building, utilizing the maximum available service life from individual materials. Adopting decisions like this can help in reducing the overall life cycle energy requirements for a building.

Therefore, this study has efficiently used the system dynamics method as an effective means in representing the interrelationships in a building's energy domain. Several such factors could be introduced in the future (e.g., cost aspects, environmental impacts) to analyze the various other interrelations existing in the building energy domain. Therefore, Chapter-6 has essentially demonstrated that the system dynamics method is fully capable of representing the interrelationships existing between different energy requirements in a building. This scheme is therefore robust enough to understand how different operation and maintenance events affect the energy use in a typical building.

Objective #3 To what extent can a life cycle based energy simulation mechanism be created by utilizing the capabilities of the new distributed co-simulation framework?

A new framework that performs an integrated life cycle energy simulation is created in Chapter-7. The building performance simulator and the occupancy behavior simulator is coupled with the energy simulator using LABS. Once initiated, this framework works automatically till the desired period (e.g., 50 years of building life time), and conducts a coupled simulation by exchanging the desired decision variables across the various simulators. The energy effects of several factors acting together in the building can be hence tested using this framework. Such a scheme is not visible in the literature so far. This framework also has the capability in extending its features by incorporating any simulator that model a dynamic behavior component.

In summary, the LABS framework has a relatively shallow learning curve, and can be easily mastered and implemented by various building practitioners, facility managers and the research professionals to create efficient and robust co-simulation systems. These types of analyses can bring more clarity on how a buildings operation need to be designed and planned for better energy efficiency. Therefore, the LABS framework is robust enough in simulating the combined effects of various energy influencing factors over a longer period of building’s life cycle, a capability not offered by any of the existing energy simulation mechanism.

9.3 Final remarks

The research in the building energy analysis domain requires a radical shift in thinking, by moving towards a distributed co-simulation approach. This is essential to analyze a building’s energy performance which is influenced by several dynamic processes that occur during the life cycle of a building such as the changing weather patterns, repair and replacement of materials, occupants' varying mix, and randomly failing HVAC systems and material assemblies, to name a few. The future energy simulations should therefore move with two goals. It should be able to incorporate the effects of various dynamic factors occurring during the entire life cycle of the building and the framework itself should have the options to connect and work across distributed systems. The current mechanism does not possess both these capabilities, and only such a framework can help understand the effects of dynamism occurring in a building's life cycle effectively.

As mentioned in the introduction chapter of this dissertation, the buildings sector is responsible for a large share of energy consumption, and schemes developed through this dissertation would be of immense help in maximizing the energy savings from the buildings sector. In addition, in an energy savings context, the tools in this domain should be easily extendable to model the energy performance of a several buildings in a community. Individual high-performing and energy efficient buildings do not mean so much if the neighborhood is wasteful. But, if an entire community is energy efficient, that is meaningful even if the individual buildings within it are not. Therefore, the future research direction should be oriented towards achieving energy efficiency at a community level to maximize the energy savings potential from the building sector.

APPENDICES

APPENDIX A: General instructions for performing a LABS framework based distributed co-simulation involving EnergyPlus and a secondary simulation program.

1. Build LCM in both the workstations using the instructions provided through LCM's web page (http://lcm-proj.github.io/).
    a. Once LCM is built in a workstation, look for the LCM installation folder. For a Windows computer, go to the WinSpecific folder and access the LCM.sln file using visual studio. This file has several individual programs in it. For example, there would be a program named lcm-example.c, and this program is written for sending a default message. Similarly, there would be a program named lcm-sink.c. This program is written to receive a message sent by lcm-example.c. For this dissertation, these two programs are modified for achieving the necessary connections between two computers. i.e., the lcm-example.c sends a message from a computer and lcm-sink.c receives that message. For a OS X or Linux machine, instead of editing the programs through visual studio file, the message sending and the receiving programs can be directly accessed through the liblcm-test folder of LCM installation.
2. Build EnergyPlus from the source code, preferably in a Windows based machine. This allows the user to access the runtime variables and the schedule values of the building

energy simulation model during runtime. For more information on this, please refer to the case study section of Chapter 5, wherein this part is addressed in detail.

   a. There are two ways of installing/building the EnergyPlus software. First way is by directly using the executable file. Second option is to build it from the source code. This method allows EnergyPlus to run through command terminal. The instructions in this website, https://github.com/NREL/EnergyPlus/wiki/Compiling-EnergyPlus can be used for building EnergyPlus from source code.

3. Develop the secondary program (e.g., occupant behavior model), in the second machine. For designing the sequence of message exchange, co-simulation and implementing the pause-wait-restart logic, refer to the methodology section described in Chapter 5 of this dissertation.

4. There will be publisher and listener programs in each workstation that come along with the installation of LCM. Modify these programs to suit the message sending and receiving needs of the problem (i.e., based on the type of message to be send across) that is being targeted to solve. Below are some snippets of the programing script written to achieve the necessary connections across the workstations.

```
char abmValues[1000];
FILE * abmData;
abmData = fopen("C:\\lcm-1.3.1\\WinSpecific\\Debug\\abmData.txt", "r");
fgets(abmValues, 1000, abmData);
fclose(abmData);
```

Figure 10-1 Reading data from Secondary program

```
if (0 == status)
{
    while (dummy == 0)
    {
        //For checking the placeholder text for sending message
        fptr = fopen("C:\\Users\\Albert\\Documents\\FILES\\EnergyPlus-8.5.0\\t
        fgets(msgTxt, 15, fptr);
        fclose(fptr);

        if (msgTxt[0] == 'A')
        {
            //Reading Eplus Data
            newfp = fopen("C:\\Users\\Albert\\Documents\\FILES\\EnergyPlus-8.5
            fgets(newLine, 300, newfp);
            fclose(newfp);
            int newDatalen = strlen(newLine) + 1;
            lcm_publish(lcm, "1234", newLine, newDatalen);

            // Writing new placeholder
            newfptr = fopen("C:\\Users\\Albert\\Documents\\FILES\\EnergyPlus-8
            if (newfptr == NULL)
                exit(1);
            fprintf(newfptr, "%s", "WAITFORABM");
```

Figure 10-2 Sending data to Secondary Program

```
if (0 == status)
    {
    while (dummy == 0)
        {
            //For checking the placeholder text for sending message
        fptr = fopen("/Users/albertthomas/lcm-1.3.1/liblcm-test/CONTROLLER.txt", "r");
        fgets(msgTxt, 15, fptr);
        fclose(fptr);


        if (msgTxt[0]== 'S')
            {
                //Data to ES
            newfp = fopen("/Users/albertthomas/Dropbox/Phd related general/Paper Writing/ABM/Journal Paper/
            fgets(newLine, 300, newfp);
            fclose(newfp);
            int newDatalen = strlen(newLine) + 1;
            lcm_publish(lcm, "12345", newLine, newDatalen);


                // Writing new placeholder
            newfptr = fopen("/Users/albertthomas/lcm-1.3.1/liblcm-test/CONTROLLER.txt", "w");
            if (newfptr == NULL)
                exit(1);
            fprintf(newfptr, "%s", "WAITFORES");
            fclose(newfptr);
```

Figure 10-3 Sending data to Primary Program

5. Connect both workstations to the same network.

6. Once the above steps are successfully completed, then the framework to perform a coupled simulation using LABS is in place.

7. Readers are encouraged to adopt the LABS framework in their own work. In such cases, it is requested that the original work be referenced by citing this study.

APPENDIX B Phase Ic- clothing schedule variations data

The data below is the clothing schedule data populated for the scenarios performed in Chapter 5.

Table 10-1 Clothing schedule data for the office working hours

ZONE-1 Clothing				
Hours	Default	Zone 1- Sc1	Zone 1- Sc2	Zone 1- Sc3
1	1	1	1	1
2	1	1	1	1
3	1	1	1	1
4	1	1	1	1
5	1	1	1	1
6	1	1	1	1
7	1	1	1	1
8	1	0.80507	0.850251	0.895418
9	1	0.812869	0.800643	0.917619
10	1	0.816308	0.810579	0.939777
11	1	0.820803	0.807964	0.94982
12	1	0.814962	0.804166	0.963921
13	1	0.813507	0.803499	1.080999
14	1	0.814891	0.803762	1.105216
15	1	0.814637	0.803607	1.116952
16	1	0.815025	0.803706	1.122884
17	1	1	1	1
18	1	1	1	1
19	1	1	1	1
20	1	1	1	1
21	1	1	1	1
22	1	1	1	1
23	1	1	1	1
24	1	1	1	1
ZONE-2 Clothing				
Hours	Default	Zone 2- Sc1	Zone 2- Sc2	Zone 2- Sc3
1	1	1	1	1
2	1	1	1	1
3	1	1	1	1

4	1	1	1	1
5	1	1	1	1
6	1	1	1	1
7	1	1	1	1
8	1	0.952023	0.930718	0.827632
9	1	1.008933	0.974097	0.828697
10	1	1.024097	0.994901	0.881349
11	1	1.030485	1.054707	0.894168
12	1	1.026028	1.083022	0.908233
13	1	1.026792	1.135801	0.955843
14	1	1.026204	1.171293	0.9555
15	1	1.025405	1.181235	0.95627
16	1	1.025946	1.182741	1.055893
17	1	1	1	1
18	1	1	1	1
19	1	1	1	1
20	1	1	1	1
21	1	1	1	1
22	1	1	1	1
23	1	1	1	1
24	1	1	1	1
ZONE-3 Clothing				
Hours	Default	Zone 3- Sc1	Zone 3- Sc2	Zone 3- Sc3
1	1	1	1	1
2	1	1	1	1
3	1	1	1	1
4	1	1	1	1
5	1	1	1	1
6	1	1	1	1
7	1	1	1	1
8	1	0.645955	0.893949	0.601324
9	1	0.548885	0.928222	0.579281
10	1	0.512547	0.938378	0.634935
11	1	0.496152	0.958089	0.633635
12	1	0.492906	0.958203	0.633736
13	1	0.494461	0.956465	0.712496
14	1	0.494525	0.956451	0.713103
15	1	0.49413	0.955882	0.713097
16	1	0.494238	0.945717	0.810327
17	1	1	1	1
18	1	1	1	1

19	1	1	1	1
20	1	1	1	1
21	1	1	1	1
22	1	1	1	1
23	1	1	1	1
24	1	1	1	1
ZONE-4 Clothing				
Hours	Default	Zone 4- Sc1	Zone 4- Sc2	Zone 4- Sc3
1	1	1	1	1
2	1	1	1	1
3	1	1	1	1
4	1	1	1	1
5	1	1	1	1
6	1	1	1	1
7	1	1	1	1
8	1	0.765357	0.681193	0.769732
9	1	0.708752	0.677999	0.795295
10	1	0.663167	0.652945	0.903528
11	1	0.651124	0.635365	0.916299
12	1	0.648218	0.59745	0.91986
13	1	0.647443	0.589643	0.983997
14	1	0.648149	0.580479	0.986652
15	1	0.648973	0.582482	0.988686
16	1	0.644497	0.582689	1.056408
17	1	1	1	1
18	1	1	1	1
19	1	1	1	1
20	1	1	1	1
21	1	1	1	1
22	1	1	1	1
23	1	1	1	1
24	1	1	1	1
ZONE-5 Clothing				
Hours	Default	Zone 5 Sc1	Zone 5- Sc2	Zone 5- Sc3
1	1	1	1	1
2	1	1	1	1
3	1	1	1	1
4	1	1	1	1
5	1	1	1	1
6	1	1	1	1

7	1	1	1	1
8	1	0.748344	0.620309	0.921096
9	1	0.74019	0.550394	0.970425
10	1	0.72843	0.512864	1.060739
11	1	0.721312	0.504204	1.103723
12	1	0.727622	0.50116	1.113821
13	1	0.726895	0.501047	1.208445
14	1	0.72617	0.501104	1.221265
15	1	0.727151	0.501105	1.227321
16	1	0.729548	0.501107	1.272356
17	1	1	1	1
18	1	1	1	1
19	1	1	1	1
20	1	1	1	1
21	1	1	1	1
22	1	1	1	1
23	1	1	1	1
24	1	1	1	1

APPENDIX C Phase Ic- Thermostat schedule variations data

The data below is the thermostat set point schedule data populated for the scenarios performed in Chapter 5.

Table 10-2 Thermostat Set point data for the office working hours

ZONE-1 Thermostat				
Hours	Default	Zone 1- Sc1	Zone 1- Sc2	Zone 1- Sc3
1	15.6	15.6	15.6	15.6
2	15.6	15.6	15.6	15.6
3	15.6	15.6	15.6	15.6
4	15.6	15.6	15.6	15.6
5	15.6	15.6	15.6	15.6
6	15.6	15.6	15.6	15.6
7	15.6	15.6	15.6	15.6
8	21	21	21	21
9	21	21.2	21.3	21.2
10	21	21.3	21	21.2
11	21	21.3	20.6	21.1
12	21	21.3	20.3	20.7
13	21	21.3	20.3	20.7
14	21	21.3	20.3	20.7
15	21	21.3	20.3	20.7
16	21	21.3	20.3	20
17	21	21	21	21
18	21	21	21	21
19	21	21	21	21
20	21	21	21	21
21	21	21	21	21
22	21	21	21	21
23	15.6	15.6	15.6	15.6
24	15.6	15.6	15.6	15.6
ZONE-2 Thermostat				
Hours	Default	Zone 2- Sc1	Zone 2- Sc2	Zone 2- Sc3
1	15.6	15.6	15.6	15.6
2	15.6	15.6	15.6	15.6

3	15.6	15.6	15.6	15.6
4	15.6	15.6	15.6	15.6
5	15.6	15.6	15.6	15.6
6	15.6	15.6	15.6	15.6
7	15.6	15.6	15.6	15.6
8	21	21	21	21
9	21	21.1	21	21
10	21	20.4	20.8	20.5
11	21	19.7	20.3	20
12	21	19	19.7	19.5
13	21	18.3	18.7	19
14	21	17.6	17.7	18.5
15	21	16.9	16.7	18
16	21	16.2	15.7	17.1
17	21	21	21	21
18	21	21	21	21
19	21	21	21	21
20	21	21	21	21
21	21	21	21	21
22	21	21	21	21
23	15.6	15.6	15.6	15.6
24	15.6	15.6	15.6	15.6
ZONE-3 Thermostat				
Hours	Default	Zone 3- Sc1	Zone 3- Sc2	Zone 3- Sc3
1	15.6	15.6	15.6	15.6
2	15.6	15.6	15.6	15.6
3	15.6	15.6	15.6	15.6
4	15.6	15.6	15.6	15.6
5	15.6	15.6	15.6	15.6
6	15.6	15.6	15.6	15.6
7	15.6	15.6	15.6	15.6
8	21	21	21	21
9	21	21.8	21.2	21.4
10	21	22	21.2	21.2
11	21	22	20.8	20.9
12	21	22	20.7	20.6
13	21	22	20.8	20.3
14	21	22	20.7	20.1
15	21	21.9	20.5	19.8
16	21	21.8	20.6	19.5
17	21	21	21	21

18	21	21	21	21
19	21	21	21	21
20	21	21	21	21
21	21	21	21	21
22	21	21	21	21
23	15.6	15.6	15.6	15.6
24	15.6	15.6	15.6	15.6
ZONE-4 Thermostat				
Hours	Default	Zone 4- Sc1	Zone 4- Sc2	Zone 4- Sc3
1	15.6	15.6	15.6	15.6
2	15.6	15.6	15.6	15.6
3	15.6	15.6	15.6	15.6
4	15.6	15.6	15.6	15.6
5	15.6	15.6	15.6	15.6
6	15.6	15.6	15.6	15.6
7	15.6	15.6	15.6	15.6
8	21	21	21	21
9	21	21.6	21.6	21.2
10	21	21.9	21.5	21.3
11	21	22	21.4	21.4
12	21	21.7	21.4	21.5
13	21	21.4	21.3	21.4
14	21	21.6	21.2	21
15	21	21.3	21	20.8
16	21	21	20.8	20.8
17	21	21	21	21
18	21	21	21	21
19	21	21	21	21
20	21	21	21	21
21	21	21	21	21
22	21	21	21	21
23	15.6	15.6	15.6	15.6
24	15.6	15.6	15.6	15.6
ZONE-5 Thermostat				
Hours	Default	Zone 5 Sc1	Zone 5- Sc2	Zone 5- Sc3
1	15.6	15.6	15.6	15.6
2	15.6	15.6	15.6	15.6
3	15.6	15.6	15.6	15.6
4	15.6	15.6	15.6	15.6
5	15.6	15.6	15.6	15.6

6	15.6	15.6	15.6	15.6
7	15.6	15.6	15.6	15.6
8	21	21	21	21
9	21	21.4	21.7	21.3
10	21	21.7	22	21.2
11	21	21.7	22.1	20.9
12	21	21.7	22.1	20.8
13	21	21.7	22.1	20.4
14	21	21.7	22.1	20.1
15	21	21.5	22.1	19.8
16	21	21	22	19.5
17	21	21	21	21
18	21	21	21	21
19	21	21	21	21
20	21	21	21	21
21	21	21	21	21
22	21	21	21	21
23	15.6	15.6	15.6	15.6
24	15.6	15.6	15.6	15.6

APPENDIX D Electrical and gas energy equation data

The data points used to populate the electricity and gas use equations in Chapter 6 is given below.

R-Value	Electricity Usage	R-Value	Gas Usage
0.57	23119.39	0.57	8390.25
0.55	23145.53	0.55	8695.45
0.54	23160.90	0.54	8850.34
0.52	23177.57	0.52	9009.84
0.51	23194.77	0.51	9172.36
0.50	23217.78	0.50	9339.59
0.48	23236.96	0.48	9510.81
0.47	23258.77	0.47	9688.41
0.46	23280.72	0.46	9870.17
0.44	23274.48	0.44	10041.40
0.43	23280.45	0.43	10216.54
0.42	23286.86	0.42	10395.46
0.41	23294.65	0.41	10578.27
0.40	23303.30	0.40	10757.41
0.39	23311.95	0.39	10941.08
0.38	23317.95	0.38	11109.77
0.37	23327.88	0.37	11296.92
0.36	23335.76	0.36	11486.74
0.35	23342.08	0.35	11597.32
0.34	23342.37	0.34	11606.32
0.33	23342.77	0.33	11619.90
0.32	23343.33	0.32	11637.41
0.31	23344.31	0.31	11658.20
0.30	23344.95	0.30	11683.30
0.30	23346.41	0.30	11706.02
0.30	23359.49	0.30	11809.29
0.30	23359.54	0.30	11823.08
0.30	23360.47	0.30	11841.56
0.30	23360.27	0.30	11859.64
0.51	23360.81	0.51	11877.99
0.49	23140.81	0.49	8932.31

0.47	23169.45	0.47	9234.17
0.46	23186.22	0.46	9396.19
0.45	23201.78	0.45	9561.30
0.44	23224.19	0.44	9736.13
0.43	23241.92	0.43	9911.44
0.41	23264.74	0.41	10091.80
0.40	23287.20	0.40	10278.03
0.39	23311.78	0.39	10465.23
0.38	23307.54	0.38	10655.18
0.37	23313.14	0.37	10839.56
0.36	23318.88	0.36	11026.46
0.35	23327.26	0.35	11211.77
0.34	23336.84	0.34	11399.40
0.34	23345.50	0.34	11590.48
0.33	23350.52	0.33	11733.57
0.32	23356.72	0.32	11929.61
0.31	23367.49	0.31	12126.71
0.30	23372.96	0.30	12247.35
0.29	23373.81	0.29	12267.29
0.57	23119.39	0.57	8390.25
0.55	23145.53	0.55	8695.45
0.54	23160.90	0.54	8850.34
0.52	23177.57	0.52	9009.84
0.51	23194.77	0.51	9172.36
0.50	23217.78	0.50	9339.59
0.48	23236.96	0.48	9510.81
0.47	23258.77	0.47	9688.41
0.46	23280.72	0.46	9870.17
0.48	23274.48	0.48	10041.40
0.46	23259.54	0.46	9730.24
0.45	23280.41	0.45	9912.56
0.44	23275.10	0.44	10086.62
0.42	23281.03	0.42	10261.82
0.41	23289.11	0.41	10442.01
0.40	23294.94	0.40	10605.16
0.39	23303.42	0.39	10786.74
0.38	23311.11	0.38	10974.27
0.37	23318.92	0.37	11159.93
0.39	23327.42	0.39	11346.84
0.38	23312.06	0.38	11025.69
0.37	23320.52	0.37	11212.12
0.36	23329.87	0.36	11402.32

0.35	23338.55	0.35	11593.31
0.34	23346.40	0.34	11705.84
0.33	23359.32	0.33	11801.46
0.32	23358.93	0.32	11810.93
0.31	23359.58	0.31	11829.03
0.30	23359.74	0.30	11849.71
0.51	23360.61	0.51	11873.89
0.49	23140.81	0.49	8932.31
0.47	23169.45	0.47	9234.17
0.46	23186.22	0.46	9396.19
0.45	23201.78	0.45	9561.30
0.44	23224.19	0.44	9736.13
0.43	23241.92	0.43	9911.44
0.41	23264.74	0.41	10091.80
0.40	23287.20	0.40	10278.03
0.39	23311.78	0.39	10465.23
0.40	23307.54	0.40	10655.18
0.39	23289.25	0.39	10349.83
0.38	23314.18	0.38	10538.72
0.37	23310.13	0.37	10728.51
0.36	23315.38	0.36	10914.71
0.36	23322.41	0.36	11104.81
0.35	23325.94	0.35	11242.76
0.34	23336.40	0.34	11433.37
0.33	23346.08	0.33	11625.81
0.32	23353.85	0.32	11818.19
0.31	23360.82	0.31	12013.43
0.57	23119.39	0.57	8390.25
0.55	23145.53	0.55	8695.45
0.54	23160.90	0.54	8850.34
0.52	23177.57	0.52	9009.84
0.55	23194.77	0.55	9172.36
0.53	23161.38	0.53	8887.42
0.52	23178.49	0.52	9048.34
0.50	23196.35	0.50	9210.84
0.49	23218.42	0.49	9380.87
0.51	23237.51	0.51	9551.00
0.50	23197.28	0.50	9253.33
0.48	23217.97	0.48	9423.31
0.47	23238.31	0.47	9595.08
0.46	23261.02	0.46	9775.26
0.48	23280.76	0.48	9958.63

0.46	23237.87	0.46	9624.72
0.45	23259.98	0.45	9808.34
0.44	23281.00	0.44	9991.49
0.43	23275.72	0.43	10167.30
0.44	23282.73	0.44	10345.68
0.43	23283.14	0.43	10045.04
0.42	23278.32	0.42	10221.28
0.41	23285.33	0.41	10400.85
0.40	23291.75	0.40	10584.56
0.42	23299.50	0.42	10768.75
0.41	23303.63	0.41	10550.61
0.39	23310.54	0.39	10728.29
0.38	23318.06	0.38	10907.69
0.37	23325.80	0.37	11091.65
0.51	23332.55	0.51	11274.97
0.49	23140.81	0.49	8932.31
0.47	23169.45	0.47	9234.17
0.46	23186.22	0.46	9396.19
0.45	23201.78	0.45	9561.30
0.46	23224.19	0.46	9736.13
0.45	23188.84	0.45	9464.04
0.44	23205.22	0.44	9632.10
0.43	23229.72	0.43	9805.83
0.42	23246.26	0.42	9981.79
0.43	23269.05	0.43	10163.36
0.42	23231.89	0.42	9879.64
0.41	23249.09	0.41	10056.38
0.40	23273.55	0.40	10239.25
0.39	23293.54	0.39	10424.99
0.40	23319.10	0.40	10621.89
0.39	23272.46	0.39	10269.74
0.38	23293.47	0.38	10461.53
0.37	23318.82	0.37	10653.85
0.36	23313.51	0.36	10847.78
0.35	23320.30	0.35	11036.28

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